

Article

Harnessing the Power of Mechanization: A Multivalued Treatment Effect Analysis on Productivity for Chinese Smallholders

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Abstract: Developing countries, in their pursuit of the Sustainable Development Goals, are intensifying their efforts to promote agricultural mechanization, with China at the forefront, through comprehensive policy revisions aimed at enhancing mechanization levels. This study employs multivalued treatment effect (MVTE) and quantile treatment effect (QTE) methodologies to assess the impact of agricultural mechanization on labor and land productivity while also examining the effects across different farm sizes and moderating influences. Leveraging data from the 2016 China Labor-force Dynamics Survey, the findings indicate that semi-mechanized and full-mechanized farming, compared to no-mechanized farming, significantly boost labor and land productivity for both average and lower-to-mid-level productivity farmers. Disaggregated analysis by farm size shows that larger farms benefit significantly from semi-mechanized and full-mechanized farming in terms of increased labor and land productivity. However, the incremental benefits of varying levels of mechanization on productivity are observed only in labor productivity for farmers with mid- and upper-level productivity and for those in the largest farm size group. Additionally, land transfer status, government subsidies, and the intensity of clan culture are found to significantly influence the productivity effects of agricultural mechanization in China. Consequently, it is imperative to reorient agricultural policies towards enhancing the efficiency and cost-effectiveness of mechanization, especially considering the constraints on labor and land availability and the need to minimize the environmental impact of agricultural production. In light of these discussions, this paper presents policy implications for sustainable agricultural mechanization.

Keywords: agricultural mechanization; labor and land productivity; multivalued treatment effect; quantile treatment effect; moderating effect; Chinese smallholders



Citation: Ma, Z.; Sun, H. Harnessing the Power of Mechanization: A Multivalued Treatment Effect Analysis on Productivity for Chinese Smallholders. *Land* **2024**, *13*, 2211. <https://doi.org/10.3390/land13122211>

Academic Editors: Dingde Xu, Shili Guo and Shaoquan Liu

Received: 1 November 2024

Revised: 11 December 2024

Accepted: 12 December 2024

Published: 17 December 2024



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1. Introduction

Maintaining and boosting agricultural productivity and income for smallholder farmers is a critical issue in many developing nations [1]. The second Sustainable Development Goal (SDG), which focuses on ending hunger and promoting sustainable agriculture, specifically targets a doubling of agricultural productivity and the income of small-scale food producers by 2030 [2]. The connection between agricultural productivity and income is well established, especially for smallholder farmers. Amidst high rates of rural-to-urban migration and an aging rural population, agricultural mechanization is key to increasing the productivity of smallholder farms, thus supporting their economic sustainability and the broader goals of sustainable agricultural development [3,4].

Since 1998, China has implemented agricultural machinery purchase subsidy policies, leading to a significant increase in the total power of agricultural machinery from 45,207.5 million kW to 105,622.1 million kW between 1998 and 2020 [5]. While mechanization shields smallholder farms from escalating labor costs, there is a growing concern that China may be overinvesting in agricultural machinery. For instance, in 2016, China used

91.54 standard tractors per thousand hectares of arable land, compared to only 27.51 in the United States [6,7]. However, a common oversight in the literature is the pivotal role of farm size. In the United States, less than 10% of farms are smaller than 10 acres, whereas, in China, at least 80% of farms are below this threshold, with land often divided into spatially separated plots [8]. The productivity and profitability derived from standard tractors vary by farm scale and plot size due to scale economies in machinery capacity. Therefore, a critical question that requires further exploration is the extent to which agricultural mechanization is linked to productivity and how this relationship might differ based on farm size in developing countries.

Agricultural mechanization is widely recognized for its positive impact on production, primarily through increased yields and output. Studies have shown that improved access to mechanization services in Ghana and the increased use of self-owned and purchased machinery services in China significantly raise crop yields [9,10]. Wang et al. further support this by demonstrating that machinery use in China leads to substantial yield increases for a variety of crops, including wheat, corn, Japonica rice, soybean, cotton, and rapeseed [11]. Belton et al. attribute the rapid rise in agricultural mechanization in Myanmar to improvements in operational speed, timeliness, weather risk management, and reduced grain loss during harvest [12]. However, it is crucial to note that farms operating on a similar scale can exhibit significant yield differences due to variations in input use efficiency, such as fertilizer application intensity. Consequently, output alone is an insufficient measure of agricultural productivity, especially when detailed information on input use and costs is lacking. This limitation also affects the assessment of the profitability and welfare impacts of agricultural mechanization on smallholder farmers.

The literature on agricultural mechanization and its impact on production efficiency is varied. Some studies emphasize the positive role of mechanization in increasing farmers' income and crop revenue by improving economies of scale [13–16]. It is also noted for its potential to alleviate poverty in regions like Zambia when implemented effectively. [14,17]. On the other hand, there is an ongoing debate about the extent to which small farms in developing countries, including those in China, can leverage the full benefits of mechanization due to the scale of available machinery [8]. The high cost of equipment is seen as a significant obstacle for these smaller operations [18]. Additionally, evidence indicates that medium-sized farms might gain more from mechanization compared to their smaller and larger counterparts, as the smallest farms typically depend more heavily on manual labor for crops [19]. This brief overview suggests that agricultural mechanization primarily benefits by alleviating rural labor deficits and leveraging scale economies of machinery. The complex interplay between mechanization and productivity, especially concerning farm size, requires deeper exploration, particularly for smallholder farmers in developing countries.

China, the world's largest developing country, has made agricultural mechanization a key driver for productivity and income growth in rural areas. The 2004 Law on the Promotion of Agricultural Mechanization, along with subsequent policies, has heightened focus on mechanization, leading to a 3.73% average annual growth rate of mechanization from 2004 to 2016 [20]. Despite a slowdown in growth since 2016, indicating a potential overinvestment in agricultural mechanization, China's Ministry of Agriculture and Rural Affairs unveiled in December 2021 plans to stabilize agricultural machinery power at around 1.1 billion kW by 2025, prioritizing optimization over expansion [21].

Facing challenges from urbanization, an aging rural population, and the rise in non-agricultural employment, which increase agricultural costs and hamper productivity, China's household-level agricultural production remains stable, contributing 29.4% to annual household income on average in 2021, with crop-planting households even more dependent on farming for income [22,23]. Agricultural mechanization in China is at a pivotal moment, demanding strategic actions that align with sustainable development and the Sustainable Development Goals. While past policies have focused on augmenting the power of agricultural machinery, there is an urgent need to shift focus towards optimizing current

machinery usage, improving mechanization efficiency, and achieving cost-effectiveness, especially in light of labor and land limitations and environmental considerations.

This study aims to address three key objectives: first, to assess how agricultural mechanization can boost labor and land productivity across different productivity levels; second, to analyze whether the impact of mechanization varies by farm size; and third, to explore the influence of land transfer status, government subsidies, and regional cultural differences on the productivity effects of agricultural mechanization. We expect to find that farmers with diverse characteristics will show asymmetric behaviors in the relationship between mechanization adoption and productivity. Utilizing data from the 2016 China Labor-force Dynamics Survey [24], encompassing 2581 rural households across 200 villages, our research reveals that semi- and full-mechanized farming, compared to no mechanization, improves labor and land productivity for average and lower-to-mid-level productivity farmers. Notably, for farmers with larger farm sizes, the adoption of semi- and full-mechanized farming significantly enhances labor and land productivity. However, the incremental benefits of different mechanization levels are only observed in labor productivity for farmers with mid-level productivity and those in the largest farm size group. These findings provide significant guidance for policymakers and stakeholders as they work towards promoting agricultural mechanization and enhancing the sustainability of smallholder farms in developing countries.

This paper makes significant contributions to the existing literature. First, it diverges from previous studies that have concentrated on a binary view of mechanization or the use of mechanization services by farmers, instead exploring the spectrum of no-, semi-, and full-mechanized farming [10,25–29]. Our analysis estimates the multivalued impact of the three mechanization strategies on labor and land productivity. Second, we leverage multivalued treatment effect (MVTE) models and quantile treatment effect (QTE) models to tackle selection bias in the mechanization adoption and assess the varied effects of mechanization in a nuanced context [30–32]. Additionally, our research underscores that the impact of mechanization is contingent upon productivity levels and farm sizes, a critical insight that is often overlooked, despite evidence indicating that larger farms and those expanding are more inclined to adopt mechanization [33,34]. This dimension is crucial for understanding the differential adoption and impact of mechanization within countries.

The rest of this paper is structured as follows: Section 2 provides the background; Section 3 details methodology; Section 4 presents the data and descriptive statistics; Section 5 displays the empirical results and its corresponding discussions; and Section 6 concludes with policy implications.

2. Background

Between 2010 and 2016, China experienced notable progress in agricultural mechanization, propelled by strategic government initiatives and technological innovations. In this section, we will discuss the key developments in agricultural mechanization, the promotion strategies that boosted mechanization levels and improved workforce capabilities, as well as the pivotal impact of non-agricultural labor on the adoption of agricultural technology and the enhancement of productivity.

2.1. Agricultural Mechanization Development

Between 2010 and 2016, China's agricultural mechanization saw remarkable progress, supported by strong data and legislative measures. The Chinese government prioritized agricultural mechanization, leading to a series of policy initiatives and subsidy measures. The "Agricultural Mechanization Promotion Law" of 2004 underscored the state's commitment to technological innovation and the dissemination of mechanization technology in agriculture. This was complemented by large-scale policy subsidies for agricultural machinery from 2005 onwards, which significantly accelerated the agricultural development.

By 2016, China's agricultural machinery power had reached 11.06 billion kilowatts, a 2.63% increase from the previous year, with the number of tractors reaching 21.44 million

units and the corresponding agricultural implements reaching 40.29 million sets. There was a notable year-on-year growth in the ownership of large and medium tractors, with increases of 12.47% and 4.24%, respectively, and the number of implements corresponding to tractors with power above 58.8 kilowatts increased by 9.65% [35].

From 2005 to 2015, the level of mechanization for major crops experienced rapid growth. By 2016, the comprehensive mechanization rate had risen to an estimated 65–66%, representing a 2–3 percentage point increase from 2015, which concluded the “Twelfth Five-Year Plan” period. This period was particularly marked by significant advancements in the mechanization of critical crops such as wheat, rice, and corn. Additionally, the advocacy for green and eco-friendly agricultural machinery emerged as a defining characteristic of this timeframe. In 2016, approximately 180,000 units of machinery, equipped with functionalities like recycling and removal, solid–liquid separation, and film residue recovery, were introduced. The establishment of the first batch of 28 full mechanization demonstration counties across the nation reached significant milestones. These included a consistent rise in the operational volume of agricultural machinery and a hastened push towards mechanization in hilly and mountainous regions. These demonstration counties have since served as a beacon, offering scalable and valuable experiences for the broader advancement of agricultural mechanization across the country.

The swift development of agricultural mechanization in China between 2010 and 2016 not only amplified agricultural production efficiency but also secured national food safety. It laid a solid material and technical foundation for the modernization of agriculture and the execution of rural revitalization strategies. This era of agricultural mechanization development was a culmination of policy promotion, technological innovation, market demand, and government subsidies, signifying a new phase in the evolution of China’s agricultural mechanization.

2.2. Mechanization Promotion

China is tackling the challenge of inadequate worker qualifications in agricultural machinery operations through a comprehensive strategy that aims to enhance both mechanization levels and worker competencies. This strategy is executed through a structured promotion system and collaborative efforts across national and local levels, thereby boosting agricultural production efficiency and modernization.

The four-tier agricultural mechanization promotion system in China is crucial for devising technology promotion strategies, implementing key projects, and converting scientific and technological achievements into practical applications. These non-profit institutions are distinguished by their public service mission, setting them apart from other service organizations.

Agricultural machinery cooperatives, established under the “Farmers’ Professional Cooperatives Law”, are pivotal in upgrading worker qualifications. Operating on principles of self-management and shared risks and benefits, these cooperatives offer a suite of services including mechanized production, harvesting, the initial processing of agricultural products, as well as information, technology, maintenance, training, and consulting services. While they generate income from services, their primary goal is to serve their members and increase agricultural production efficiency rather than to maximize profits.

The Chinese government has introduced policies and regulations to foster the transformation and upgrading of the agricultural mechanization and equipment industry. These initiatives aim to establish an efficient mechanized production system, promote mechanization-compatible crop varieties, and create conditions for full-process mechanization and large-scale production. By encouraging the integration of information technology in agricultural machinery and operations, the quality and efficiency of agricultural machinery operations are significantly enhanced.

Acknowledging the small-scale nature of Chinese rural landholdings, China emphasizes the use of medium and small-sized machinery in the mechanization process, often operated by more professional villagers or those with extensive experience within agri-

cultural machinery cooperatives. This approach ensures that the qualification issue is less critical than the level of mechanization, as each rural household can select the appropriate level of mechanization to meet their needs, supported by promotion organizations, cooperatives, company personnel, and other rural family members.

2.3. Contributions of Non-Agricultural Labor Force

When examining agricultural mechanization, the primary goals are to boost productivity and decrease the labor required for farming tasks. However, it is essential to recognize the significant interplay between mechanization and non-agricultural labor. This relationship is not just important but also pivotal, as non-agricultural labor can influence the adoption and advancement of agricultural mechanization within specific economic and social contexts.

The “semi-agricultural, semi-non-agricultural” employment model is a strategic adaptation to the seasonal demands of agricultural labor, which results in periods of low demand and prompts rural workers to seek non-agricultural work during the off-season [36]. This model helps maintain a balance between agricultural and non-agricultural work. The Chinese government’s initiative to redirect surplus agricultural labor into non-agricultural sectors, as detailed in the State Council’s “Notice on the Promotion of Employment Planning (2011–2015)”, has significantly increased job opportunities in rural areas. This policy has been instrumental in localizing non-agricultural employment, providing workers with the flexibility and variable work schedules necessary to engage in peak agricultural activities alongside their non-agricultural jobs. The 2016 third agricultural census data, compared to 2018, show a relatively low average household ownership of key agricultural machinery, highlighting the reliance on non-agricultural labor to support agricultural work, especially when mechanization is limited [37].

The influence of non-agricultural employment on agricultural productivity extends beyond just labor availability. During our research period, internet usage in rural China was not as widespread, emphasizing the importance of knowledge and information exchange for the adoption of new agricultural technologies. Non-agricultural workers, through their interactions in various work environments, are more likely to acquire and disseminate knowledge that advances agricultural technologies, thereby enhancing productivity. Despite concerns that non-agricultural work might impede the adoption of labor-intensive advanced practices [31], China’s agricultural technology extension organizations and agricultural machinery cooperatives coordinate technology promotions and operations, reducing the need for every household to undergo agricultural machinery operation training.

Economically, non-agricultural employment significantly impacts agricultural production efficiency by increasing remittances and raising household income levels [38]. This income growth can alleviate income constraints for family members remaining in agriculture, enabling them to invest in more capital-intensive and labor-saving agricultural production factors to enhance labor productivity. While there is evidence that increased non-agricultural income can lead to increased agricultural investment [39,40], it is also observed that farmers may allocate these funds to home construction, children’s education, and other durable goods consumption [41]. However, in the context of small-scale farming in China, where farmers tend to purchase mechanical services rather than machinery for self-operation, the financial support from non-agricultural labor effectively increases investment in agricultural production, particularly in covering the costs of mechanical services, to a certain extent.

3. Econometric Specification

In this study, we followed the framework to specify the impact of agricultural mechanization on labor and land productivity [31,42]. In the MVTE model, for each household i ($i = 1, \dots, N$), we observed Y_i (labor and land productivity), T_i (multivalued mechanization strategy, where $T = 1$ for no-mechanized farming, $T = 2$ for semi-mechanized farming,

and $T = 3$ for full-mechanized farming), and X_i (the vector of pre-treatment covariates, such as age, education, gender, farm size, and household size). The set (Y_{i1}, Y_{i2}, Y_{i3}) indicates the potential productivity level for each household i where $T_i = t$ and $t \in \{1, 2, 3\}$, given that only one of Y_{it} is observed once a specific mechanization strategy is selected. Each observed outcome Y_i can be written as a function of the treatment indication D_{it} and potential outcome Y_{it} as follows:

$$Y_i = \sum_{t=1}^3 D_{it}(T_i)Y_{it}, \quad D_{it}(T_i) = \begin{cases} 1, & \text{if } T_i = t \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Let m and n denote the distinct mechanization strategies, such that the treatment effect (τ) of strategies m versus n can be expressed as the difference between potential outcomes associated with these strategies:

$$\tau = E(Y_{im} - Y_{in}), \quad m, n \in t = \{1, 2, 3\} \quad (2)$$

The MVTE model employs the ignorability and overlap assumptions to create the semblance of randomness [42]. The ignorability assumption implies that the choice of mechanization strategy is uncorrelated with the crop income outcomes. This assumption holds once we partial out a rich set of observed pre-treatment characteristics (X) by drawing on the existing literature. The overlap assumption requires that, for the setting of covariates (X) in the assumed population, there is a chance of seeing households in all mechanization strategy groups in contrast. We used the multinomial logit (MNL) model to estimate the generalized propensity score (GPS) as the conditional probability of a household belong to a particular mechanization strategy group conditioning on X_i [43] and employ the GPS to weigh observations and estimate the treatment effects.

Given the selected covariates (X), the conditional expectations of the potential productivity outcomes for mechanization strategies m and n are $E[Y_{it}|X_i] = E[Y_i|T_i = t, X_i] = \beta_{0t} + X_i'\beta_{1t}$, where $t = m$ and n , respectively. Therefore, the average treatment effect (ATE) of adopting mechanization strategy m versus n over the whole population can be estimated as follows:

$$ATE_{mn} = \frac{1}{K} (E[Y_{im}|X_i] - E[Y_{in}|X_i]) \quad (3)$$

where K refers to the total number of observations that take part in the treatment $T_i = m$ and $T_i = n$, $m, n \in t = \{1, 2, 3\}$. We employed an inverse-probability-weighted regression adjustment (IPWRA) estimator to estimate both average treatment effects as the IPWRA estimator has a double-robust property to ensure the treatment effects estimated are consistent and unbiased [30,32].

We also study a weighted quantile regression approach for estimating the conditional quantile labor and land productivity. Let $F_{Y_t}(Y)$ be the distribution function of the potential productivity outcomes $Y(t)$, $t = \{1, 2, 3\}$. For $0 < \tau < 1$, the τ th quantile of the T potential productivity outcomes are $q(\tau) = \{q_1(\tau), q_1(\tau), q_2(\tau)\}'$, where $q_t(\tau) = F_{Y_t}^{-1}(\tau) = E[F_{Y_t|X}(Y_t|X)]$, and $F_{Y_t}(Y)$ is assumed to be continuous. Therefore, the quantile treatment effect (QTE) of adopting mechanization strategy m versus n over the whole population can be estimated as follows:

$$QTE_{mn,\tau} = \frac{1}{K} (q_m(\tau) - q_n(\tau)) \quad (4)$$

where K refers to the total number of observations that take part in the treatment $T_i = m$ and $T_i = n$, $m, n \in t = \{1, 2, 3\}$. Again, we form GPSs generated from an MNL model and construct the IPWRA estimator by using an inverse-probability-weighted regression adjustment scheme. The quantile regression framework estimates the heterogeneity in treatment effects at the lower (0.25), median (0.5), and upper (0.75) quantiles of the distribution of labor productivity and land productivity, which allow us to obtain a more

complete picture of the multivalued treatment effects of agricultural mechanization on the productivity outcomes.

The productivity effects of agricultural mechanization are significantly influenced by the land transfer status of farmers, the extent of government subsidies received, and the variations in clan culture within their local regions. Consequently, it is anticipated that farmers with different combinations of these characteristics will exhibit asymmetrical relationships between mechanization adoption and productivity. To test this hypothesis, we incorporate interaction terms into our analysis. The specific model is as follows:

$$Y_i = \alpha_0 + \alpha_1 \text{Mechanization}_i \times \text{Moderator}_i + \alpha_2 \text{Mechanization}_i + \alpha_3 \text{Moderator}_i + \sum \text{Controls}_i + \sum \text{Province}_i + \varepsilon_i \quad (5)$$

where Y_i represents, respectively, labor productivity and land productivity, and moderator variables are employed to adjust the relationship between mechanization and productivity outcomes. These moderators include the household's land transfer status, the government subsidy receipt, and the intensity of clan culture in the village of residence. The land transfer status is quantified by the proportion of the household's contracted land to the total arable land. The receipt of government subsidies is measured using a binary variable from the survey data, indicating whether the household has received any government subsidies. The intensity of clan culture in the village is assessed by the population proportion of the most common surname in the village.

4. Data and Descriptive Statistics

We use China Labor-force Dynamics Survey (CLDS) data collected in 2016 for empirical analysis [24]. The data were collected and owned by the Center for Social Survey at Sun Yatsen University, Guangzhou, China. A multistage cluster, stratified, and probability-proportional-to-size sample of China labor force was surveyed, and the surveys provided information on households and individuals in both rural and urban communities in China (except Hong Kong, Taiwan, Macau, Tibet, and Hainan). Screened by the questions about agricultural operations in 2015, the dataset used in this study includes a total of 2581 farmer households involved in crop planting in 2015. This sample comprises 834 households adopting no mechanized farming (i.e., farm machines are not used at any production stages), 1077 adopting semi-mechanized farming (i.e., farm machines are used at some production stages), and 670 adopting full-mechanized farming (i.e., farm machines are used at every production stage).

First, it is important to note that our analysis, which concentrates on grain crops, is limited by the CLDS 2016 data that provided information on agricultural income rather than direct agricultural output. Therefore, we used the crop income (output value) per unit of labor or land to represent labor and land productivity [44,45]. We define crop income as returns over cash costs, which is the value of the crop outputs produced by the household minus the value of paid-out costs of crop planting. The crop outputs are valued even if a small portion of the production is consumed by the farmer's household rather than sold on the market. Given that most small farms in China rent or share the machinery they use [46], the depreciation costs can be neglected [47]. This measure of income based on returns over cash costs adequately represents the crop income available to the household at the end of the cropping season. The survey instrument elicited information on a household's 2015 wage income, property income, transfer income, and, most importantly, agricultural income after subtracting all expenses, and, in this study, we focus on agricultural income for crop planting farmers.

We further examine agricultural labor productivity and land productivity through crop income per effective agricultural labor and per mu, where 1 mu equals 1/15 hectare. Agricultural labor productivity is usually measured by the number of units of outputs produced per unit of labor or the number of hours effectively worked in the process of production. However, the reported change in the number of hours does not always reflect the change in technology and, therefore, productivity [48]. We employ a questionnaire item inquiring, "Last year, how many people in your household were engaged in agricultural

production for more than three months?”. Using this, we developed an effective agricultural labor indicator. We defined all eligible laborers in a household who worked in agricultural production for over three months as constituting one unit of agricultural labor. Those who did not meet this threshold are counted as 0.5 units, and we aggregated these to determine the total effective agricultural labor force for each household. This approach allows us to quantify the labor contribution to agriculture, taking into account the varying degrees of engagement with agricultural activities. An increase in the productivity of effective agricultural labor results in an increase in the net cash farm income at no additional monetary cost. Expressed in monetary units, crop income per effective agricultural labor is used in our analysis to explore the effect of agricultural mechanization on labor productivity.

Agricultural land productivity, as the most applicable productivity measure in the context of cropping activities, measures the crop production generated by a given unit of land. An increase in land productivity reflects a higher output per unit of land and higher farm income. Therefore, in this study, we used the crop income per mu to represent the agricultural land productivity in monetary units.

To capture the labor and land productivity, we calculated the per effective agricultural labor and per mu crop income for each household and used their logarithmically transformed values in the analysis. Agricultural mechanization was assumed to help foster labor and land productivity and, therefore, the productivity in monetary units. Figure 1 demonstrates the means and 95% confidence intervals of labor and land productivity by the mechanization strategies. With an upgrade in mechanization strategy, labor productivity increases consistently, while land productivity exhibits a difference between no-mechanized farming and mechanized farming with no notable incremental increase.

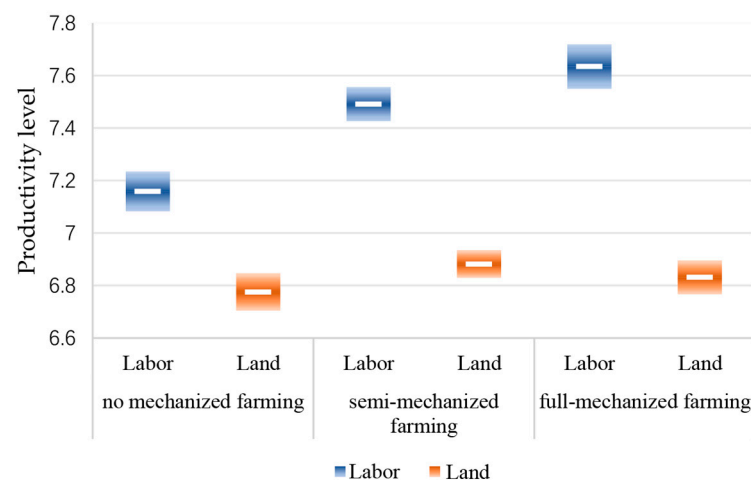


Figure 1. Productivity across the three mechanization strategies with 95% confidence intervals. The labor and land productivity are measured by using the logarithmically transformed value of per effective agricultural labor and per mu crop income for each household.

Figure 2 displays how the labor and land productivity are distributed by the mechanization strategies. By using kernel density estimation to create smooth approximations, we are able to visualize and compare the productivity distributions for different mechanization strategies. For labor productivity, the peak shifts to the right and becomes lower as the mechanization level improves, which implies that the labor productivity distribution has a higher average and a higher variance with mechanized farming. However, as revealed in Figure 2, there is no notable change among the peak values of land productivity distributions, while the concentration from the peak grows much more intense as the mechanization level improves. We note that the observed difference between the labor and land productivity distribution changes can be attributed to different farm sizes and the different ways that agricultural practices are involved with mechanization based on farm size as reported by the surveyed smallholder farmers. In this sense, the disaggregated

analysis by farm size of the productivity improvement effect of agricultural mechanization is necessary and imperative.

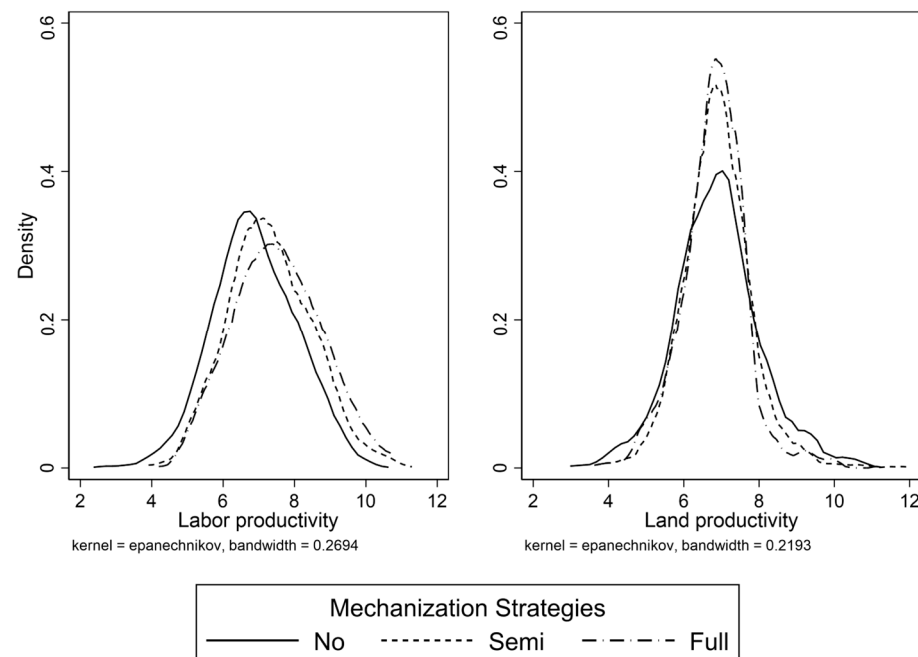


Figure 2. Kernel density plots of labor and land productivity for different mechanization strategies.

As shown in Table 1, we find that almost 68% of farms (1747 out of 2581) adopt agricultural mechanization, while 26% of them apply full-mechanized farming. If we narrow our focus and categorize the data based on farm size into three tertiles, the distribution of the adoption of mechanization strategies among the three groups show that, as expected, smaller farms are less likely to adopt mechanization, while larger farms are more likely to.

Table 1. Farm-size characteristics and distribution of agricultural mechanization strategy.

Variables	Mean (μ)	S.D. (μ)	Obs. on Mechanization Strategies			Total Obs.
			No	Semi	Full	
Farm size	7.88	6.39	834	1077	670	2581
lower tertile	2.89	0.83	399	350	179	928
median tertile	6.17	1.17	277	359	221	857
upper tertile	15.55	6.26	158	368	270	796

Furthermore, to control the spatial changes in mechanization level and productivity level in crop production, Table 2 shows the regions and provinces of China covered in our analysis, as well as the corresponding distributions of farm sizes and mechanization levels of the sample farms from these regions. The inter-regional distinctions of distributions of the farm size and the mechanization level were not drastic in our sample, but Western China, where small farms account for a higher proportion, has a lower rate of mechanization applications. In all, farm size plays an active role in agricultural mechanization adoption, but how the farm size influences the productivity improvement effect of agricultural mechanization needs more in-depth study.

We also utilize the question, “What is the situation regarding the mechanized production tools used by your household?”, which provides options such as ownership, co-purchase, rental, borrowing, and other arrangements. This question is integrated into our regression model to gain insights into the diverse methods that farmers utilize mechanization and its effect on production efficiency.

Table 2. Geographic distribution of farm size and agricultural mechanization strategy.

Region	Province	Farm Size (Tertile)			Mechanization Strategy			Obs.
		Lower	Median	Upper	No	Semi	Full	
eastern	Tianjin; Hebei; Liaoning; Jiangsu; Zhejiang; Fujian; Shandong; Guangdong; Guangxi	419	349	318	284	494	308	1086
central	Shanxi; Neimenggu; Jilin; Anhui; Heilongjiang; Jiangxi; Henan; Hubei; Hunan	227	256	310	225	363	205	793
western	Sichuan; Chongqing; Guizhou; Yunnan; Shanxi; Gansu; Ningxia; Xinjiang	282	252	168	325	220	157	702

We acknowledge that regional factors like soil conditions, climate, irrigation, and predominant crop types could influence the impact of mechanization on productivity. To account for these, we included them as control variables in our model. Specifically, for irrigation conditions, we relied on responses to “From January 2015 to now, has the growth period (before harvest) of crops in this village required irrigation?” and “From January 2015 to now, what has been the main irrigation method in this village?”. Soil improvement conditions were identified through the question “Has soil modification been implemented in this village?”. The dummy variable for region was used to control climatic variations.

The scope of mechanized farming in this study is confined to grain crops. Drawing from the 2016 White Paper on Agricultural Mechanization Development in China, we note that, while the mechanization level for economic crops is lower than for grain crops, the overall mechanization rate for major national crops is anticipated to be between 65 and 66% [35]. Thus, we believe that our focus on grain crops will not significantly skew the results due to crop type differences.

Table 3 presents summary statistics for the main variables used in our empirical analysis. The average household head is 55 years and has an education level between primary school and middle school. The average household has 4.68 members and owns 2.11 mu of crop land per family member. An amount of 63% of households have land use certificates issued by the government.

Table 3. Variable definitions and descriptive statistics.

Variables	Definitions	Mean	S.D. ¹	Min	Max
Dependent variables					
Labor productivity	Log of crop income per effective agricultural labor	7.57	1.11	3.00	11.29
Land productivity	Log of crop income per mu ²	6.83	0.93	3.22	10.77
Treatment variable					
Mechanization strategies	1 = no-mechanized farming; 2 = mechanized farming	1.68	0.47	1	2
	1 = no-mechanized farming; 2 = semi-mechanized farming; 3 = full-mechanized farming	1.94	0.76	1	3
Control variables					
Age	Age of household head (HH) in years	54.97	10.54	24	96
Gender	1 if HH is male, 0 otherwise	0.92	0.26	0	1
Education	Educational levels ³ of HH in years	2.53	0.98	1	9
Health status	Self-reported health status (from 1 = very unhealthy to 5 = very healthy)	2.53	1.05	1	5
Household size	Number of people in a household	4.68	2.01	1	16
Farm size per labor	Farm size cultivated by a household (mu/labor)	2.11	2.50	0.13	30
Land use certificate	1 if household receives a formal land use right certificate, 0 otherwise	0.63	0.48	0	1
Migrant worker	The proportion of migrant worker among labor aged between 15 and 64 in a village (%)	0.28	0.20	0.01	1
Planting plan	1 if there exists a planting plan in a village, 0 otherwise	0.29	0.45	0	1

Table 3. Cont.

Variables	Definitions	Mean	S.D. ¹	Min	Max
Pest control	1 if there exists pest control service in a village, 0 otherwise	0.37	0.48	0	1
Agri-tech training	1 if there exists agri-technology training service in a village, 0 otherwise	0.69	0.46	0	1
Cooperative	1 if there exists an agricultural cooperative in a village, 0 otherwise	0.27	0.44	0	1
Distance to town	Log of (distance from household location to town + 1)	1.71	0.66	0	3.93
Machine ownership	1 if fully household-owned, 2 co-owned, 3 fully leased, 4 borrowed, 5 mixed owned and leased/borrowed, 6 mixed owned and co-owned, 7 other, 8 no machinery used	4.62	2.56	1	8
Mechanization services	1 if there is mechanization service in a village, 0 otherwise	0.13	0.33	0	1
Irrigation	1 if the growth period (before harvest) of crops in a village required irrigation, 0 otherwise	0.71	0.45	0	1
Irrigation method	1 if flood, 2 if drip, 3 if sprinkler, 4 if other irrigation methods, 5 if no irrigation needed	2.55	1.77	1	5
Soil modification	1 if there is soil modification in a village, 0 otherwise	0.13	0.33	0	1
Eastern	1 if household locates in Eastern China, 0 otherwise	0.42	0.49	0	1
Central	2 if household locates in Central China, 0 otherwise	0.31	0.46	0	1
Western	3 if household locates in Western China, 0 otherwise	0.27	0.45	0	1

¹ S.D. refers to standard deviation. ² 1 mu = 1/15 hectare; ³ 1 = illiterate; 2 = primary school; 3 = middle school; 4 = high school; 5 = vocational high school; 6 = technical school; 7 = technical secondary school; 8 = college; 9 = bachelor.

5. Results and Discussions

5.1. The Effect of Dichotomous Mechanization Strategies

We first estimate the impact of agricultural mechanization on the labor and land productivity by considering a dichotomous decision of farm machine use (Table 4). The GPS with the MNL model is applied where the dependent variable is, whether or not the farm uses machines. Following previous studies [30,42], we further estimate the percentage change in the ATE and the QTE to make the interpretation of the coefficient estimates straightforward.

Table 4. Average treatment effect and quantile treatment effects of adopting mechanization (IPWRA estimator).

	Labor Productivity		Land Productivity	
	ATE	% Δ	ATE	% Δ
MF vs. NMF	0.180 (0.051) ***	2.824	0.159 (0.054) ***	2.370
	QTE (Q25)	% Δ	QTE (Q25)	% Δ
MF vs. NMF	0.297 (0.064) ***	4.493	0.362 (0.076) ***	6.026
	QTE (Median)	% Δ	QTE (Median)	% Δ
MF vs. NMF	0.223 (0.055) ***	3.022	0.176 (0.082) **	2.617
	QTE (Q75)	% Δ	QTE (Q75)	% Δ
MF vs. NMF	0.134 (0.077) *	1.628	0.062 (0.053)	0.846

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard error in parentheses. MF refers to mechanized farming; NMF refers to no-mechanized farming; % change is calculated by expressing the treatment effects as the percentage of the estimated potential outcome means.

As displayed in the first column, adopting agricultural mechanization can increase labor productivity by 2.824% on average, compared to no-mechanized farming. In addition to mean treatment effects, estimating quantile treatment effects reveals that the agricultural mechanization affects the smallholder farmers at the lower end of the labor productivity distribution differently than it affects those in the middle and those at the upper end. To be more precise, the mid-level farmers see a significant 3.022% increase in labor productivity, the lower-end farmers achieve a significant 4.493% increase, while the impact is considerably less pronounced, at a mere 1.628% increase on the upper quantile farmers.

Similarly, mechanized farming significantly increases land productivity by 2.370% on average. For lower-end farmers, mechanized farming increases land productivity by 6.026%, compared to no-mechanized farming. Upper-end farmers do not appear to derive statistically significant benefits from agricultural mechanization in terms of land productivity.

The estimated mean treatment effects agree with the existing literature regarding the effect of agricultural mechanization on productivity improvement [9–12], while the estimated quantile treatment effects further reflect a more versatile and informative relationship between agricultural mechanization and labor/land productivity. However, these results still fail to reflect on both the effect of various agricultural mechanization levels and the effect variation in farm sizes, both of which will be further demonstrated below.

5.2. The Effect of Three Types of Mechanization Strategies

By applying the MVTE model, we are able to assess the heterogeneous effects of mechanization in a multivalued context. Table 5 reports the estimation results for Equations (3) and (4), controlling additional variables that may influence the agricultural productivity and regional heterogeneity. Again, we calculate the percentage change in the ATE and the QTE to ease understanding.

Table 5. Average treatment effect and quantile treatment effects of adopting mechanization strategy *m* vs. adopting mechanization strategy *n* (IPWRA estimator).

<i>m</i> vs. <i>n</i>	Labor Productivity		Land Productivity	
	ATE	% Δ	ATE	% Δ
SMF vs. NMF	0.186 (0.055) ***	2.499	0.178 (0.058) ***	2.654
FMF vs. NMF	0.256 (0.061) ***	3.439	0.152 (0.063) **	2.266
FMF vs. SMF	0.070 (0.050)	0.918	−0.026 (0.048)	−0.378
	QTE (Q25)	% Δ	QTE (Q25)	% Δ
SMF vs. NMF	0.297 (0.069) ***	4.493	0.356 (0.081) ***	5.926
FMF vs. NMF	0.297 (0.083) ***	4.493	0.370 (0.089) ***	6.159
FMF vs. SMF	0.000 (0.067)	0.000	0.015 (0.090)	0.236
	QTE (Median)	% Δ	QTE (Median)	% Δ
SMF vs. NMF	0.167 (0.073) ***	2.467	0.160 (0.084) *	2.379
FMF vs. NMF	0.310 (0.094) ***	5.040	0.176 (0.085) **	2.617
FMF vs. SMF	0.143 (0.077) **	2.565	0.015 (0.038)	0.218
	QTE (Q75)	% Δ	QTE (Q75)	% Δ
SMF vs. NMF	0.049 (0.088)	0.790	0.081 (0.057)	1.105
FMF vs. NMF	0.118 (0.085) ***	3.244	0.032 (0.058)	0.437
FMF vs. SMF	0.069 (0.088) **	2.448	−0.049 (0.056)	−0.661

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard error in parentheses. SMF refers to semi-mechanized farming; NMF refers to no-mechanized farming; and FMF refers to full-mechanized farming. The % change is calculated by expressing the treatment effects as the percentage of the estimated potential outcome means.

For labor productivity, as shown in the second and third columns of Table 5, we find significantly positive average treatment effects of agricultural mechanization on productivity when compared with no-mechanized farming. The output indicates that changing the mechanization strategy from no-mechanized farming to semi-mechanized farming results in a significant enhancement in labor productivity by 2.499%, and the effect of changing the mechanization level from no to full-mechanized farming is a 3.439% increase in labor productivity. The 0.25 quantile results indicate that semi- and fully mechanized agriculture raises labor productivity equally by 4.493% for the lower-end farmers. The median results show that the labor productivity gap between semi-mechanized or fully mechanized agriculture and non-mechanized agriculture is 2.467% and 5.040%, respectively, with a significant incremental impact of agricultural mechanization of 2.565%. In contrast, for the upper quartile of farmers, the 0.75 quantile results show that they only reap significant benefits from fully mechanized farming, which improves their labor productivity.

Our results show that, compared to no-mechanized farming, farmers with the lower labor productivity benefit most from mechanization, while no statistically significant

incremental effect is found from semi- to full-mechanized farming. This is reasonable given that the farm performance with the lower productivity labor is far from being economically or technically efficient, and any small changes in how farm operations are performed, either through semi- or full-mechanized farming, will lead to large increases in output and income, therefore improving the labor productivity. When the labor productivity upgrades from lower quantile to mid-level, not only will both semi- and full-mechanized farming significantly improve labor productivity relative to no-mechanized farming, but there will exist a significant incremental effect of mechanization on labor productivity improvement. Farmers with mid-level labor productivity may have relatively better access to and understand new knowledge and farmer training, such that they may better grasp the general level of farm management required by the full-mechanized farming [49], hence enjoying the incremental effect of mechanization on labor productivity. However, it is only full-mechanized farming that significantly enhances labor productivity among the higher-labor-productivity farmers. This insight prompts a deeper investigation into the production constraints confronting smallholder farmers in China. These farmers may have reached a level of technical efficiency where only full mechanization can further propel productivity gains. This scenario is particularly relevant in developing countries, where limitations on inputs beyond labor, such as farm size, can impede the enhancement of marginal labor productivity even with semi-mechanization. The constraints on land and other factors of production mean that the potential for labor productivity improvement through partial mechanization is limited, and, thus, only the transition to full mechanization can break through these barriers and unlock additional efficiency.

For land productivity, compared to no-mechanized farming, results displayed in the fourth and fifth columns of Table 5 show that semi- and full-mechanized farming significantly increase land productivity by 2.654% and 2.266%, respectively. The estimated quantile treatment effects indicate that lower-end farmers benefit much more in land productivity from semi- or full-mechanized farming than mid-level farmers. The difference (5.926%, 6.159%) is more than twice as much as those for the mid-level farmers (2.379%, 2.617%). An increase in land productivity is synonymous with more efficient farming practices with agricultural machinery, that is, if everything else is held equal. Based on the law of diminishing marginal productivity, the additional return generated by an upgrade in agricultural mechanization level declines the higher the land productivity is. One in particular is that, failing to reject hypotheses and joint hypotheses that state that semi- and full-mechanized farming bring the same treatment effects within and across means and quantiles, we cannot conclude that a higher level of mechanization has a larger improvement effect on land productivity. The result can also be observed in Figure 3. Though farmers are expected to benefit more from adopting a high level of mechanization, the finding suggests that no incremental effect of agricultural mechanization has been found on land productivity in our analysis.

As intuition would suggest, smallholder farmers, even with higher land productivity in our analysis, are not necessarily technically efficient. To explain the non-existence of the land productivity improvement effect of mechanization for the upper-end farmers, the farmers may need to use more of a certain type of input, such as agricultural infrastructure improvement and land holding increase through land consolidation, to reach prescribed technical efficiency upgrades. Thus, simply implementing the policy on the basis of the positive mean treatment effects might have caused unintended consequences on individual farmers.

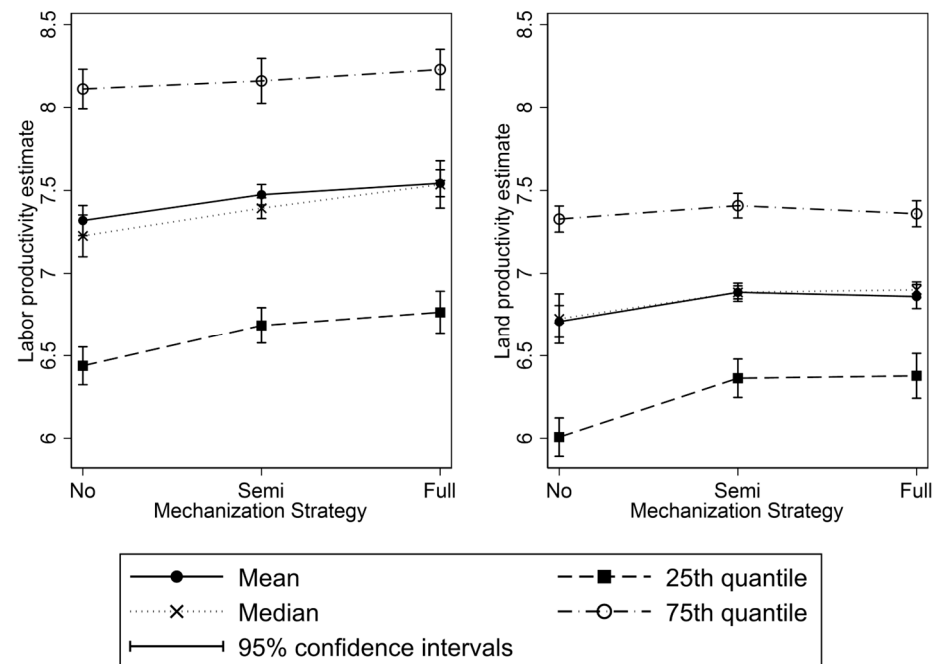


Figure 3. Estimated means and quantiles for mechanization strategies.

5.3. Disaggregated Analysis by Farm Size

Results displayed in Table 6 show that there exist heterogeneous effects of mechanization adoption on productivity by farm size. Farmers in the highest tertile of farm size are more likely and able to adopt agricultural machinery, therefore benefiting most from mechanized farming on both labor and land productivity. The significantly positive impacts of mechanization, though much smaller, sustain for the farmers in the median tertile of farm size, but diminish for the farmers in the lowest tertile of farm size. And no incremental effect of the agricultural mechanization is found for farmers in these two groups.

Table 6. Disaggregated analysis by farm size (IPWRA estimator).

<i>m</i> vs. <i>n</i>	Labor Productivity		Land Productivity	
	ATE	% Δ	ATE	% Δ
lower tertile				
SMF vs. NMF	0.055 (0.083)	0.780	0.009 (0.086)	−0.127
FMF vs. NMF	0.014 (0.092)	0.198	−0.042 (0.093)	−0.594
FMF vs. SMF	−0.041 (0.090)	−0.577	−0.051 (0.091)	−0.720
median tertile				
SMF vs. NMF	0.267 (0.077) ***	3.645	0.202 (0.074) ***	3.029
FMF vs. NMF	0.256 (0.096) ***	3.494	0.172 (0.092) *	2.579
FMF vs. SMF	−0.011 (0.082)	−0.145	−0.030 (0.079)	−0.437
upper tertile				
SMF vs. NMF	0.357(0.106) ***	4.530	0.406 (0.105) ***	6.492
FMF vs. NMF	0.500 (0.103) ***	6.345	0.510 (0.102) ***	8.155
FMF vs. SMF	0.143 (0.073) *	1.736	0.104 (0.071)	1.562

*** $p < 0.01$, * $p < 0.1$; robust standard error in parentheses. SMF refers to semi-mechanized farming; NMF refers to no-mechanized farming; and FMF refers to full-mechanized farming. The % change is calculated by expressing the treatment effects as the percentage of the estimated potential outcome means.

For labor productivity, relative to no-mechanized farming, semi-mechanized farming increases that of farmers in the highest tertile of farm size by 4.530%, while full-mechanized farming significantly increases labor productivity by 6.345% with a notably and significantly incremental effect of agricultural mechanization. For land productivity, both full- and semi-mechanized farming bring the largest significant increases of 6.492% and 8.155%,

respectively, to farmers in the largest farm size group, which are more than twice the size of effects for farmers in the median tertile of farm size, though no incremental effect is found. On one hand, mechanization can vastly reduce the time and effort of many agricultural production practices. Larger land holdings enable the more proper and better utilization of agricultural machines which further improve labor productivity [50,51]. On the other hand, along with the standardized improved seed use, chemical fertilizer use, and pesticide use, the adoption of agricultural mechanization can provide more efficient input management and therefore confer the competitive benefits to smallholding farmers from the efficiencies gained by land productivity improvement [52,53]. Thus, the disaggregated analysis by the farm size of agricultural mechanization on productivity offers the smallholding farmers a key means to eke out a sustainable, high-productivity agricultural production.

Figure 4 illustrates the confidence interval outcomes for the quantile treatment effects of mechanization on both labor and land productivity, segmented into three tertiles based on land size. The semi-mechanized versus no-mechanized comparison is denoted by the blue line/area, while the full-mechanized versus no-mechanized comparison is indicated by the orange line/area. The sequence from left to right represents an ascending order of land size, with the corresponding regression results showing an overall trend of increasing significance across farm size tertiles. This suggests that the efficacy of mechanization is contingent upon its harmonious integration with land size.

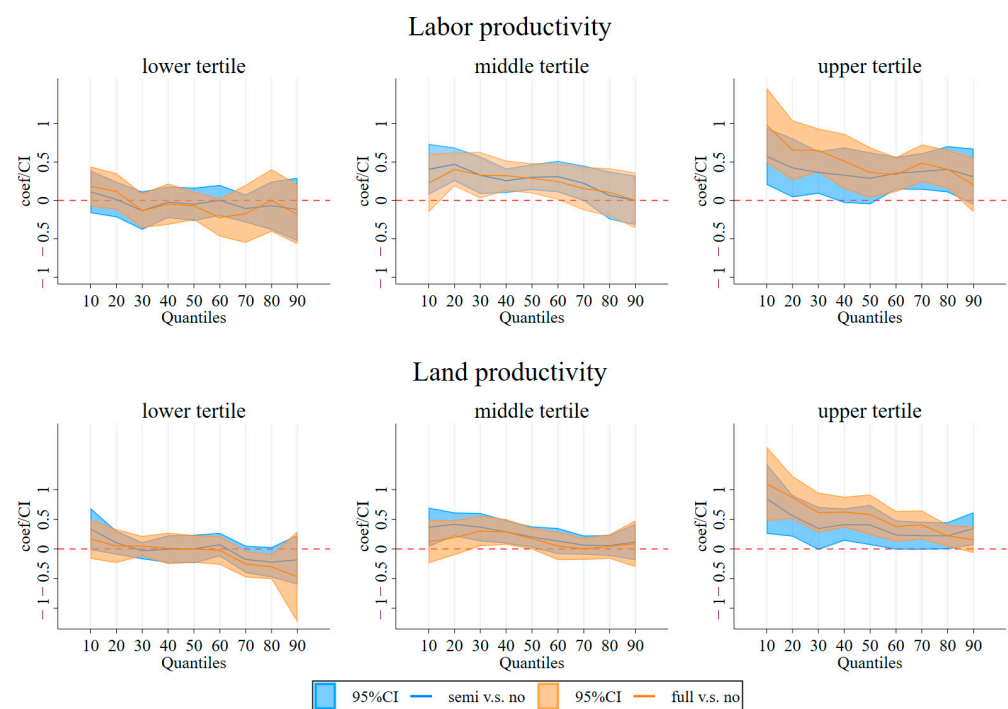


Figure 4. Quantile treatment effects of mechanization on labor and land productivity across tertiles of land size.

Within the upper tertile, the estimated effects for full mechanization exceed those for semi-mechanization, and they exhibit greater statistical significance, indicating the superiority of full mechanization over semi-mechanization. In the medium land size tertile, the impacts of full and semi-mechanization are comparatively indistinguishable. Regardless of the land size, the downward trajectory observed in the quantile treatment effect results, along with the diminishing significance, implies that mechanization has a more substantial marginal effect on the productivity of low-productivity farmers, encompassing both labor and land aspects.

5.4. Moderating Effects

The productivity effects of agricultural mechanization are significantly influenced by several key factors, including the land transfer status of farmers, the receipt of government subsidies, and the prevalence of clan culture in the local region. Specifically, the land transfer status is measured by the ratio of a household's contracted land to its total cultivated land. The presence of government subsidies is indicated by a dummy variable derived from survey data, reflecting whether the household has received any subsidies. The intensity of clan culture in a village is quantified by the population proportion of the most common surname within the village. In our regression analysis shown in Table 7, we controlled for provincial fixed effects and employed robust standard errors.

Table 7. Moderating effects.

	(1)	(2)	(3)	(4)	(5)	(6)
	Labor Productivity	Land Productivity	Labor Productivity	Land Productivity	Labor Productivity	Land Productivity
Contracted * Mechanization	0.069 *** (0.014)	0.150 *** (0.053)				
Contracted	−0.003 (0.022)	−0.289 ** (0.118)				
Subsidy * Mechanization			0.132 ** (0.056)	0.107 * (0.055)		
Subsidy			−0.195 * (0.115)	−0.200 * (0.113)		
ComLastNam * Mechanization					−0.150 (0.104)	−0.190 * (0.101)
ComLastNam					−0.054 (0.233)	0.270 (0.226)
Mechanization	0.140 *** (0.029)	0.076 *** (0.028)	0.066 (0.051)	0.016 (0.049)	0.229 *** (0.052)	0.170 *** (0.050)
Constant	7.469 *** (0.489)	7.367 *** (0.585)	7.592 *** (0.500)	7.493 *** (0.587)	7.560 *** (0.518)	7.349 *** (0.598)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.395	0.133	0.395	0.132	0.397	0.132
N	2581	2581	2581	2581	2581	2581

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard error in parentheses; ComLastNam denotes the prevalence of the dominant last name within the village's population, reflecting clan culture.

As detailed in Table 7, the findings reveal that households that have acquired additional land through transfers experience an increased effect of mechanization on labor and land productivity. This suggests that larger landholdings facilitate the more efficient use of machinery and improved resource management, thereby enhancing both productivity measures.

Furthermore, the receipt of government subsidies is found to significantly amplify the enhancing effect of mechanization on both land and labor productivity. Subsidies are crucial in making mechanization more affordable and in promoting the adoption of advanced technologies, which, in turn, leads to substantial improvements in productivity across both dimensions.

In contrast, a more prevalent clan culture tends to diminish the land productivity-enhancing effects of mechanization. This reduction may be attributed to the adherence to traditional farming practices, social patterns of resource allocation, or a resistance to innovation within these communities. These findings highlight the intricate interplay of factors when integrating mechanization into agricultural practices, emphasizing the necessity of considering socio-economic and cultural factors in the quest for enhanced agricultural efficiency and productivity.

6. Conclusions

Given the substantial improvement in the mechanization level of major economic crops, China's agricultural mechanization remains in a developmental phase. To achieve sustainable agricultural production, it is imperative to scrutinize the impact of agricultural mechanization on the productivity of China's smallholder farmers. This analysis is essential for formulating continuous development measures and strategies aimed at promoting the adoption of mechanization and enhancing its economic impact on agricultural production. Utilizing data from the 2016 China Labor-force Dynamics Survey (CLDS), this study employs a multivalued mechanization framework—encompassing no-mechanized, semi-mechanized, and full-mechanized farming—to investigate the impact of agricultural mechanization in China. This framework addresses the uneven distribution of mechanization efforts among smallholder farmers, overcoming information loss about the nature of mechanization's impact.

By applying the MVTE model and QTE model, we explore the average treatment effect, quantile treatment effect, the disaggregated analysis by farm size, and the moderating effect of agricultural mechanization on both labor and land productivity. This approach provides extensive and nuanced insights into the relationships between agricultural mechanization and labor/land productivity. The empirical results are as follows:

The empirical results show that (1) general agricultural mechanization significantly improves both labor and land productivity on average, particularly for lower- and mid-level productivity farmers; (2) the multivalued mechanization framework reveals that, compared to no-mechanized farming, both semi- and full-mechanized farming have significantly positive impacts on labor and land productivity for lower- and mid-level productivity farmers; (3) disaggregated analysis by farm size indicates that, compared to no-mechanized farming, both semi- and full-mechanized farming significantly increase labor and land productivity for farmers with larger farm sizes; (4) the incremental productivity improvement effect of different levels of mechanization is observed in labor productivity for farmers with mid- and upper-level labor productivity and for those in the largest farm size group; and (5) land transfer status, government subsidies, and the intensity of clan culture significantly influence the productivity effects of agricultural mechanization in China. According to the empirical results, there are four policy implications.

Firstly, addressing the potential overinvestment in agricultural mechanization, our analysis suggests that the efficiency of agricultural machinery is crucial, which is related to the actual production capacity when factors such as production quality control, agricultural labor, and farm size are considered. Given the fragmented and scattered landholdings in China, it is essential to assist smallholder farmers of all productivity levels by providing access to highly adaptable and reliable machinery. Policy tools that improve machine-appropriate agricultural practices and promote the integration of agricultural machinery and agronomy are vital for enhancing the crop-output expansion and national food security effects of sustainable agricultural mechanization.

Secondly, the level of agricultural mechanization for lower productivity farmers in China should be further improved. The empirical results show a significant improvement effect of mechanization on both labor and land productivity for lower productivity farmers, where small farm size has not yet become a major limitation of production. More policy attention should be directed towards the initial adoption of mechanization for these farmers, rather than comprehensive mechanization plans. However, a basic plan for the structure and cultivation of the agricultural labor force is needed to assist farmers in becoming aware of, adopting, and improving the use of mechanization to boost production efficiency, income, and welfare in the near future as labor and land productivity upgrade.

Thirdly, the productivity improvement effect and incremental effect of agricultural mechanization vary among the three farm size groups in our analysis. Consistent with many related studies, this result implies that enlarging the farm size would enhance the productivity improvement effect of mechanization, given that larger farms permit a better use of agricultural machinery. While China has been promoting land consolidation, implement-

ing an overall plan for the development of high-standard farmland, establishing functional areas for grain production and protected areas to produce important agricultural products, and efforts to cultivate socialized service organizations and agricultural cooperation that help farmers rent or share machinery should be further strengthened. This guidance is essential for steering smallholding farmers onto the track of modern agriculture.

Above all, government subsidies are instrumental in rendering mechanization more affordable and in catalyzing the adoption of cutting-edge technologies, which are essential for markedly boosting productivity in both land and labor. In tandem with this, acknowledging and addressing the cultural nuances that shape mechanization outcomes are critical. Policymakers must craft strategies that not only alleviate the resistance to mechanization in communities with deeply rooted traditional practices but also actively promote the adoption of modern farming techniques. Moreover, incorporating socio-economic and cultural considerations into policy formulation is imperative for bolstering agricultural efficiency and productivity. By adopting a holistic approach, mechanization initiatives can be better aligned with the distinct needs and circumstances of various farming communities, fostering a more effective and inclusive trajectory for agricultural advancement.

Our study, though insightful, is bound by the data available up to 2016. Beyond this point, China's agricultural mechanization has advanced markedly, especially with the pronounced increase in micro-tiller sales, which captured 30.54% of the market share in 2021. Additionally, the total power of agricultural machinery increased to 10.71 billion kilowatts in 2021, marking a 1.42% rise and signaling further developments in mechanization that our research does not encompass. Nevertheless, our findings lay a robust foundation for subsequent research and policy formulation. China's "14th Five-Year Plan" for agricultural mechanization aims to maintain the total machinery power at approximately 11 billion kilowatts by 2025. This plan emphasizes the refinement of machinery allocation, the enhancement of operational environments, and the establishment of a comprehensive agricultural machinery socialized service system. It also underscores the advancement towards larger, smarter, and more versatile agricultural machinery, aligning with the broader initiative to converge mechanization with information and intelligent technologies. We aspire for our research to catalyze effective mechanization strategies in developing countries and to enrich the international dialogue on agricultural modernization.

Author Contributions: Conceptualization, Z.M. and H.S.; methodology, Z.M. and H.S.; software, Z.M.; validation, Z.M.; formal analysis, Z.M. and H.S.; investigation, Z.M. and H.S.; resources, Z.M. and H.S.; data curation, Z.M. and H.S.; writing—original draft preparation, Z.M. and H.S.; writing—review and editing, Z.M. and H.S.; visualization, Z.M. and H.S.; supervision, H.S.; project administration, H.S.; funding acquisition, H.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Fundamental Research Funds for the Central Universities, Zhongnan University of Economics and Law, grant number 2722024BQ045.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

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