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ORIGINAL ARTICLE

Machinery structure, machinery subsidies, and agricultural productivity: Evidence from China

Meng Meng[1,2] | **Leng Yu**[1] | **Xiaohua Yu**[2]

[1]Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai, China

[2]Department of Agricultural Economics and Rural Development, University of Göttingen, Göttingen, Germany

Correspondence
Xiaohua Yu, Department of Agricultural Economics and Rural Development, University of Göttingen, Germany, 10.121. Platz der Göttinger Sieben 5, 37073, Göttingen, Germany.
Email: xyu@gwdg.de

Abstract

Although agricultural machinery is indispensable for modern agriculture, the effect of machinery structure on food production is rarely scrutinized. Machinery structure, referring to the proportion of high-capacity machines which are represented by tractors with relatively high horsepower, is used to measure the scale of agricultural machinery. In response, this article investigates how agricultural machinery structurally impacts grain production theoretically and empirically, with particular emphasis on the effects of capacity structure and subsidy policy. The article estimates a Translog production function with a panel dataset covering 126 counties across Xinjiang and Hubei provinces in China from 2002 to 2012. Though we find the general elasticity of output with respect to machinery inputs is .03, the capacity structure of agricultural machines could impact agricultural production by inducing the reallocation of other input factors. Along with the upsizing of farming machines, we observe the complementarity between machinery horsepower and land inputs in production increases, while the joint effect of machinery and fertilizer decreases. The positive land channel is found in areas with fewer high-capacity machines, while the negative fertilizer channel occurs when there are more large machines.

KEYWORDS
agricultural mechanization, agricultural subsidy, capacity structure effect, food security, grain production

JEL CLASSIFICATION
Q16, Q18

1 | INTRODUCTION

How technology promotes agricultural production and ensures food security is an important research topic. It is the investment in agricultural technology that transforms traditional agriculture and facilitates agricultural modernization, thereby contributing to worldwide economic growth (Schultz, 1964). Agricultural machinery is one of the key technologies to promote food production and facilitate urbanization and industrialization by saving agricultural labor forces. The different endowments of natural resources and supportive policies lead to a divergence

pace of agricultural mechanization between countries all over the world. According to the induced technology innovation hypothesis, developed countries with large-scale farms, represented by the United States, rely heavily on large-scale mechanization to produce food (Binswanger, 1986; Ruttan & Hayami, 1971). According to the Census of Agriculture in 2017, more than 75% of tractors in the United States have more than 40 horsepower, and almost 31% of the tractors have more than 100 horsepower (USDA, 2019). While in Japan, most tractors sold are mid-sized tractors with 21–30 horsepower capacity.[1] As for China, following the classification criteria in statistical yearbooks and many previous studies, small tractors usually have engines less than 14.74 kW (20 horsepower), while large tractors refer to tractors with power capacity over 36.78 kW (50 horsepower) and medium tractors lay between the above (Chen & Lan, 2020; Jetté-Nantel et al., 2020; Liu et al., 2014).

Apart from highly mechanized developed countries, divergent patterns also exist in developing areas like Asian and African countries. Furthermore, the heterogeneous scales of agricultural machines keep changing over time (Benin, 2015; Diao et al., 2020; Lu et al., 2022). Asia and Northern Africa witnessed rapid agricultural mechanization after the 1960s. The exponential increase of tractors in Asia in the 2000s can be partly explained by the diffusion of pedestrian tractors, a type of small tractor. However, in sub-Saharan Africa, the efforts to promote mechanization mostly failed in the 1960s and 1970s (Benin, 2015). The shares of rural households with access to tractors are all below 5% in several selected sub-Saharan African countries (FAO, 2022).

Recognizing the limited availability of detailed information on agricultural machinery types, there exists a knowledge gap in understanding the effects of agricultural mechanization on food production particularly regarding tractor size. In this article, we use machinery capacity structure to capture the proportion of large-sized agricultural machinery. Specifically, since most specific farm tools and machines need to be used with tractors, we use the share of large/medium tractor size based on horsepower or quantity to proxy the machinery structure. Clarifying the impact of machinery structure on production is conducive to improving agricultural machinery subsidy and industrial policies in developing countries so that machines can better match local production patterns and improve productivity.

This issue is particularly important when it comes to the case of China where arable land per capita is relatively scarce and fragmented for smallholders, especially in traditional farming regions, in contrast to most mechanized countries with large-scale machines and land operations, such as the United States. Growing food demand and limited production capacity jointly challenge China's self-sufficiency policy and highlight the importance of domestic food security issues. Agricultural mechanization is raised as a key factor in promoting agricultural modernization and ensuring food security in China. The scale of farming machines is closely related to the development of mechanical technologies. Large tractors, along with their supporting machines and parts, are recognized as symbols of advanced technology and agricultural mechanization. The rapid change of the tractor size in China provides a suitable case for this article.

Since the establishment of the People's Republic of China in 1949, different stages of agricultural mechanization with different attitudes towards large-scale or small-scale machinery (Chen & Lan, 2020). The adoption of large tractors gained momentum during the period of large collective farms and experienced a reversal following the implementation of the Household Responsibility System, resulting in the prevalence of small machinery. Since 2004, the government has implemented a subsidy policy for agricultural machinery purchases, which has sequentially improved mechanization growth in both public and private sectors. The Agricultural Machinery Purchase Subsidies (AMPS) initially targeted 66 main grain production counties in 2004 due to financial constraints (Lu et al., Zhang et al., 2020). The targeted counties have increased year by year and the AMPS gradually expanded to cover all counties nationwide by 2009. The total amount of subsidies has increased from 70 million yuan in 2004 to 19 billion yuan in 2021. Since the AMPS program tends to favor large machinery, and cross-regional social services increase the demand for large agricultural machinery, the number of large tractors has been rapidly increasing. Nevertheless, studies show that small tractors may be more profitable and adapted to small farm sizes, thus reducing the mechanization divide in smallholder economies in Asia (Baudron et al., 2015; Daum, 2023; Kahan et al., 2018). Given the difference between theory and practice in China, we wonder how the machinery structure affects grain production in China.

In response, this article analyses the direct, indirect, and capacity structure effects of agriculture machinery on production theoretically and decomposes the structure effects into land, labor, and fertilizer channels. Then we employ a panel dataset of 126 counties in Xinjiang and Hubei province from 2002 to 2012 to empirically estimate the effects. The county-level dataset fits the topic better than household-level data because it is hard to calculate the machinery structure of one household or even

[1] Data source: Statistics of production and shipment of agricultural machinery in Japan from the Japan Agricultural Machinery Manufacturers Association (JAMMA). http://jfmma.or.jp/e/trendsstatistics_e.html

households aggregated at the village level. Only a few large farmers or cooperatives can purchase various tractors of different sizes, whose tractors' working radius can cover the arable land of several villages. The limitation of farm tractor scale in household-level data determines that the county-level data are more suitable. The reason why we use data in Xinjiang and Hubei provinces is that only in these two provinces were we able to collect comprehensive and uninterrupted tractor power structure data. This is due to the scarcity of available mechanical statistics and the incongruity in machinery indicators across counties, particularly the lack of different types of agricultural machinery at the county level. After matching the input factors with the mechanical structure and eliminating the missing value, the balanced panel dataset is constrained to these two provinces. We use a fixed-effects model in conventional OLS regression and a time-varying true fixed-effects (TFE) model in stochastic frontier analysis (SFA) to estimate the Translog production function and examine the structure effects of machinery on food output. The inversed probability weight (IPW) method is also utilized to alleviate the endogeneity problem of the machine structure. The research also includes the subsidy policy indicator to explore the role of supportive subsidy policy in food security.

This article mainly contributes to three strands of literature. First, it adds to the literature on mechanization and, more broadly, to technology adoption and diffusion. The innovation of technology significantly has a positive effect on economic growth, as is indicated by theoretical models like induced innovation theory, human capital theory, and agricultural treadmill theory (Cochrane, 1958; Hicks, 1963; Hume, 1907; Ruttan & Hayami, 1971; Schultz, 1964). Later empirical research has focused on different specific technologies, including seed, irrigation, fertilizer, and what we care about the most, machinery (Bravo-Ureta et al., 2020; McArthur & McCord, 2017; Smale et al., 2018; Yang et al., 2013; Zhang et al., 2017). According to the induced innovation theory, mechanization investments, especially in large tractors, may only pay off for large farms (Otsuka, 2013).

However, practical experience in China, where the average farm size is below one hectare, has shown that there are various forms of mechanization: ownership, rental, and outsourcing services. China's steadily increasing farm output over the past decades is associated with mechanization despite land fragmentation and a rapid decline in the agricultural labor force (Yang et al., 2013). Outsourcing services have helped to solve the problem of smallholder farms not achieving the threshold of scale economy due to the indivisibility of large machines. However, the role of the machinery power structure in this process has not been sufficiently researched. To our knowledge, Liu et al. (2014) disaggregate machinery inputs into large, medium, and small categories, defined by horsepower, and investigate the heterogeneous substitution among labor and three categories of machinery at a household level in China. Another literature that is closely related to our study is Foster and Rosenzweig (2022). They utilize economies of scale in the capacity of power sprayers to explain the continued rise in agricultural productivity with farm scale at the right tail of the U-shaped curve, where higher-capacity machines are matched to large farms and can work at full capacity at lower costs. In our study, we focus on the effect of high-capacity tractors on grain production and the mismatch between large tractors and sown areas in China.

Second, we specifically shed light on the structure effect of agricultural machinery on farm output and food security by estimating a Translog production function. Many studies use Translog cost or production functions to estimate the elasticity of various inputs and the substitution (Lin et al., 2022; Liu et al., 2014; Lu et al., 2022; Tian et al., 2020; Yi et al., 2019; Yu, 2012). The effects of mechanization on planting area, off-farm employment, labor, and production efficiency are broadly studied (Ji et al., 2012; Ma et al., 2021; Qing et al., 2019). Agricultural machinery services even change the combination of inputs in the production function, thus having a certain impact on economies of scale and economies of scope (Takeshima, 2017; Takeshima et al., 2020). Our article builds on the foundation that agricultural machinery affects grain production not only directly but also indirectly through its influence on land, labor, and fertilizer inputs. Furthermore, we analyze the impact of machinery capacity structure on this indirect effect.

Third, our article is connected to the literature on the role of government subsidies in farming production. Huang et al. (2013) have analyzed a range of subsidy programs in China, encompassing those related to grain, input, seed, and machinery, using survey-based microdata. They found that the number of farmers who benefited from mechanization subsidies was limited and that machinery subsidies were mainly reserved for larger machines purchased by high-income households, which only accounted for a small share of purchases. Other research has examined the effects of different types of agricultural subsidies, including the Hundred Billion Plan and Granary County Subsidy in China (He et al., 2019; Lin & Huang, 2021; Yi et al., 2015; Zhang et al., 2020; Zou et al., 2020). However, the limited scale of mechanization and its subsidies have led to less attention on their impacts in the literature. Misallocation in agricultural production could cause the loss of productivity. While Zhang et al. (2023) and Zhong et al. (2023) particularly shed light on the misallocation in land market in China, the misallocation of machinery inputs has not been well examined in the literature. In this article, we argue that machinery subsidies are a vital control

variable when analyzing the effect of machinery power structure on crop production. As an intermediate capital input, the agricultural machine's influence on production may be underestimated in the previous literature.

Our article makes two contributions to the literature. First, we incorporate the structure of agricultural machinery into the theoretical model and clarify the structure effect of farming machines on grain production. Using the Translog production function, we illustrate the heterogeneous leverage effects of mechanical structures through land, labor, and fertilizer channels on output after controlling for the pilot of machinery subsidies. Second, we provide solid evidence of misallocation between large farming machines and small sown areas, highlighting that upsizing machinery does not consistently lead to higher technical efficiency. Our research shows that the promotion of large agricultural machinery should be adapted to local conditions and the historical biases favoring large-scale tractors should be carefully reconsidered, particularly for agricultural departments of governments in developing countries with smaller land scales.

2 | BACKGROUND AND RESEARCH HYPOTHESIS

2.1 | Agricultural mechanization in China

China is the world's largest grain producer, managing to feed roughly 20% of the global population with only 7% of the world's arable land. Maize, rice, and wheat are the major grain crops in China. Chinese cropping systems are based on grain production and are highly diverse from north to south, including single, double, and triple cropping (Zhang et al., 2015). There are both single and double cropping in Xinjiang, and the cereal-cotton rotation system is widely practiced there. While in Hubei, the double-cropping system is dominant, such as the rice-wheat and double-rice system. The sown area of grain crops accounts for 71% in China, 56% in Hubei, and 46% in Xinjiang in 2012.

Agricultural mechanization contributes to the sustained increase in grain production. The development of Chinese agricultural mechanization is inextricably linked to economic reform and institutional evolution, with different policies being implemented during different stages of economic development. Since the establishment of the People's Republic of China in 1949, the process can be divided into five phases: startup (1949–1978), transformation (1979–1990), transition (1991–2003), acceleration (2004–2014), and readjustment (2014–present). Despite the initial hardships during the startup phase, the total power of farm machinery surpassed 10 billion kW by 2020, a significant increase from the mere 81 thousand kW in 1949.[2] In the startup phase (1949–1978), the government focused on the development of large machinery, as scale farms were equipped with large tractors under the People's Commune System.

However, due to its low productivity, the centralized planned economy began to disintegrate and was replaced by the Household Responsibility System (HRS) after the economic reform in 1978. During the second phase (1979–1990), the number of small tractors increased from 1.67 million to nearly 7 million, while the growth of large tractors was relatively slow. The transformation of ownership allowed farmers to purchase farm machines independently, which was confirmed and supported by the central government in 1984. Chen and Lan (2020) pointed out the proliferation of small tractors was suitable to local factor endowments and farm size, whereas the plummeting use of tractors also symbolized a kind of stagnation of agricultural mechanization and modernization.

In the third phase (1991–2003), the government began to promote green technologies like straw returning and no-tillage sowing, as well as the emergence of agricultural machinery outsourcing services. Until 2003, over 30 million households owned agricultural machines.

After transitioning to a market-oriented economy, China's agricultural mechanization entered a new historical stage of acceleration based on the Law of the People's Republic of China on the Promotion of Agricultural Mechanization. In 2004, the central government established a special fund to subsidize the purchase of agricultural tractors and tools, marking the beginning of the "Golden Decade." By 2014, the number of large and medium-sized tractors had increased by 407.71% compared to 2004, reaching nearly 5.68 million. Meanwhile, the number of small tractors grew slowly, with a total increase of 2.75 million units from 2004 to 2011, and the number even began to decline since 2011, with a total decrease of 815,000 units in three years.

The accelerating promotion of farming machines largely resulted from the Agricultural Machinery Purchasing Subsidies (AMPS). The subsidy program was implemented county by county from 2004, starting with 66 counties in 16 provinces, and gradually expanding to cover all counties nationwide by 2009. The fund mainly comes from the central government, which can cover up to 30% of the cost of farmers' purchases. The total fund for the subsidy increased from 70 million in 2004 to 13 billion in 2009. The total fund of machinery subsidies remained at 9.1 billion yuan in 2021, accounting for nearly 18% of the total sales price, and subsidizing over 1.31 million machines and tools, benefiting more than 975,000 smallholders and

[2] Data resource of total power and quantity of tractors in this paper are from the database on the website of National Bureau of Statistics in China. https://data.stats.gov.cn/easyquery.htm?cn=C01

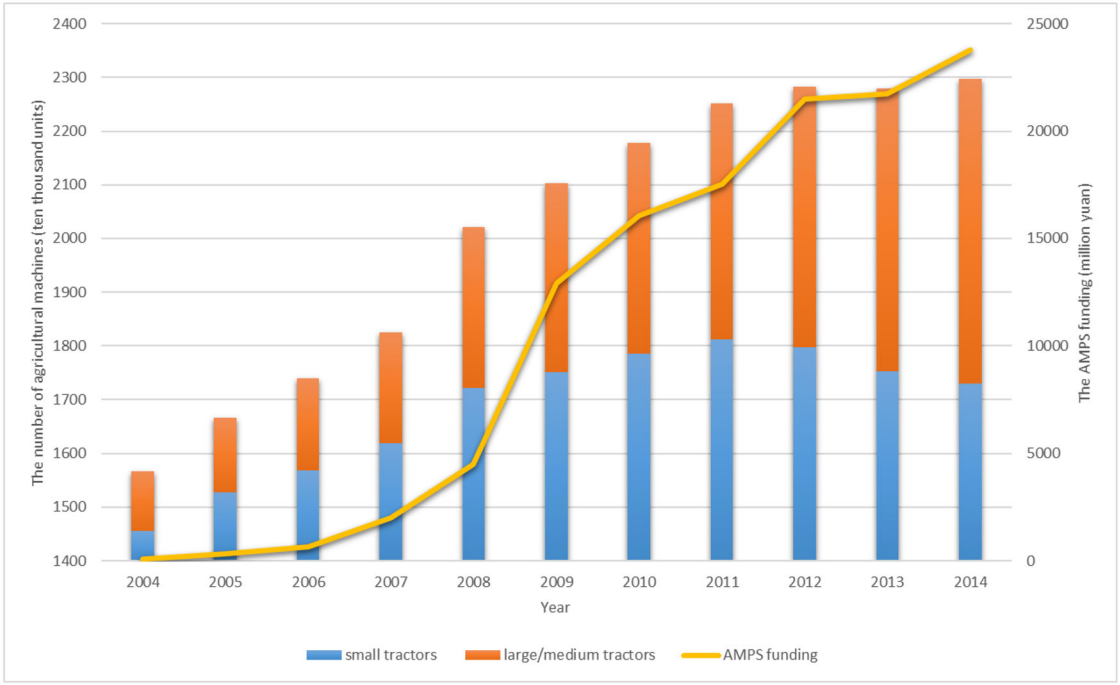

FIGURE 1 The development of different types of agricultural tractors and AMPS funding in China from 2004 to 2014.

Note: The bars depict the number of large and small tractors in China from 2004 to 2014. Small tractors have engines of less than 14.74 kW. Large tractors refer to tractors with power capacity over 36.78 kW (50 horsepower). Medium tractors lay between the above. Small tractors usually have engines of less than 14.74 kW. The line shows the funding of the Agricultural Machinery Purchase Subsidies (AMPS) program each year. Data are from the *China Agricultural Machinery Industry Yearbook*.

service organizations.[3] Figure 1 illustrates the development of various sizes of agricultural tractors and the funding of the AMPS during this period in China. However, the growth rate of tractors and tools slowed down after 2014, indicating a need for policy readjustment.

In this article, we mainly focus on the acceleration stage (2004–2014), during which China switched its agricultural policy from extraction to protection. Modern tractors and tools were rapidly adopted during this period, and the size of tractors was undergoing dynamic changes, providing a typical and historical context for our analysis. In addition, we use the relative exogenous machinery subsidies program to identify the effect of tractor size on farm production more clearly.

2.2 | Research hypothesis

The article mainly estimates the internal structure effect of farming machines on grain production, which can be theoretically divided into three input channels: land, labor, and fertilizer. With the increase in the size of agricultural machinery, the diffusion of larger tractors may replace rural labor, cause land consolidation, and introduce collectivized social services. It is estimated that elasticities of substitution between labor and large machinery are greater than those between labor and smaller machinery categories (Liu et al., 2014). Thus high-capacity machinery weakens the leverage effect of machinery on production through the labor channel. Closely related to outsourced services, large agricultural machinery can encourage farmers to transfer land in through the labor substitution effect (Qian et al., 2022), as well as promote production by indirectly increasing crop sown area.

The structure effect of machinery on agricultural production in the fertilizer channel is complicated. The study of Sun et al. (2021) reveals a U-shaped pattern in the marginal value product of fertilizer with its increasing usage. Given China's fertilizer intensity, saving fertilizer results in reduced output contribution from chemical fertilizer in most Chinese contexts (Foster & Rosenzweig, 2022). Firstly, tractors with high power capacity in large farms can be efficiently integrated with high-quality agricultural parts and machinery, leading to reduced operational time and fertilizer savings. Moreover, large tractors are capable of effectively executing deep soil preparation and facilitating subsequent field management. The

[3] The data source of agricultural machinery subsidy is from the agricultural machinery purchase subsidy information disclosure column in the website of Ministry of Agriculture and Rural Affairs. http://www.amic.agri.cn/subsidy/btzx/182

joint effect of machinery and fertilizer on production is positively influenced by the stronger complementarity of high-capacity tractors and fertilizer, while it is negatively affected by reductions in fertilizer application. Secondly, large-scale mechanization also affects the crop varieties cultivated by farmers, subsequently impacting the amount of chemical fertilizer used. With the application of large tractors, the cultivated areas of corn and soybean in China continue to expand, compared to wheat and rice. The phenomenon is also evident in Xinjiang and Hubei provinces. In general, maize and soybean are relatively less fertilizer-intensive than other grain crops, especially during 2004–2013 when corn's contribution to the annual change in fertilizer intensity was negative due to shifts in the structure of crops produced, which is another potential reason for the lower cross-effect of machinery and fertilizer (Sun et al., 2021). However, distinguishing the joint effects becomes increasingly intricate when considering different fertilizer types from the perspective of adjusting crop varieties. Therefore, the structure effect of machinery on farm output in the fertilizer channel depends on the trade-off between the above mechanisms.

In summary, machinery structure plays a crucial role in agricultural production. Using high-capacity machinery could augment the land inputs, leading to positive complementary effects of machinery and land inputs on grain production. Additionally, high-capacity machinery also has the potential to replace labor inputs. The joint effect of machinery and labor input is expected to decrease grain production. However, the cross-effect of machinery and fertilizer is uncertain based on the preceding analysis. Therefore, we propose the following hypothesis:

The structural effect of machinery on grain output via the land channel is positive; the effect on grain output through the labor channel is negative; while the effect on grain production via the fertilizer channel remains indeterminate.

3 | THEORETICAL MODEL AND ECONOMETRIC METHODS

To explore the structural effect of the machinery on production, we construct a theoretical model derived from a production function with four inputs and one output. The four input factors of the function are referred to Gong (2018), following the general setup. That is,

$$Y = y(L, M(s), N, Z) \tag{1}$$

where Y is the agricultural output; L, M, N, and Z denote farm land input, machinery, labor, and fertilizer, respectively. s refers to the machinery structure, and $M(s)$ captures the idealized feature that machinery structure only indirectly affects other inputs and therefore grain output through the total horsepower M.[4] Taking total differentiation for Equation (1), the effect of machinery input on production can be easily presented:

$$\begin{aligned}\frac{dY}{dM} &= \frac{\partial y}{\partial M} + \frac{\partial y}{\partial L}\frac{\partial L}{\partial M} + \frac{\partial y}{\partial N}\frac{\partial N}{\partial M} + \frac{\partial y}{\partial Z}\frac{\partial Z}{\partial M} \\ &= \frac{\partial y}{\partial M} + \sum_{i\in\{L,N,Z\}} \frac{\partial y}{\partial X_i}\frac{\partial X_i}{\partial M}\end{aligned} \tag{2}$$

where $\frac{\partial y}{\partial M}$ can be defined as the direct effect of machinery on production when other factors are fixed; While the second part of the decomposition is the indirect effect of farm machines on farm output that is always ignored in the empirical analysis. In this part, i represents other three inputs besides machinery.

The development of mechanization will affect grain production by changing the allocation of other inputs. There are substitution or complementation relationships between input factors. Farming machinery, as the representation of advanced production technology, could cause the adjustment of all the inputs. Then we introduce machinery structure (s) to the basic model. Mathematically, Equation (2) can be rewritten in the equivalent form as follows:

$$\begin{aligned}\frac{dY}{dM} &= \frac{\partial y}{\partial M}\Big|_{s\ fixed} + \frac{\partial y}{\partial s}\frac{\partial s}{\partial M} + \frac{\partial y}{\partial L}\frac{\partial L}{\partial s}\frac{\partial s}{\partial M} + \frac{\partial y}{\partial N}\frac{\partial N}{\partial s}\frac{\partial s}{\partial M} \\ &+ \frac{\partial y}{\partial Z}\frac{\partial Z}{\partial s}\frac{\partial s}{\partial M} = \frac{\partial y}{\partial M}\Big|_{s\ fixed} + \frac{\partial s}{\partial M}\left(\frac{\partial y}{\partial s} + \frac{\partial y}{\partial L}\frac{\partial L}{\partial s} + \frac{\partial y}{\partial N}\frac{\partial N}{\partial s} + \frac{\partial y}{\partial Z}\frac{\partial Z}{\partial s}\right) \\ &= \frac{\partial y}{\partial M}\Big|_{s\ fixed} + \frac{\partial s}{\partial M}\left(\frac{\partial y}{\partial s} + \sum_{i\in\{L,N,Z\}}\frac{\partial y}{\partial X_i}\frac{\partial X_i}{\partial s}\right)\end{aligned} \tag{3}$$

The final form of Equation (3) consists of two parts: $\frac{\partial y}{\partial M}|_{s\ fixed}$ indicates the direct effect of farm machines on production when other factors and machinery structures are all controlled; $\frac{\partial s}{\partial M}(\frac{\partial y}{\partial s} + \sum_{i\in\{L,N,Z\}}\frac{\partial y}{\partial X_i}\frac{\partial X_i}{\partial s})$ shows how the structure of agricultural machinery affects production, which can be further divided into two sections. $\frac{\partial s}{\partial M}\frac{\partial y}{\partial s}$ means the change of farm machines will impact the internal structure change of large and small tractors, resulting in variation in production. And $\frac{\partial s}{\partial M}\sum_{i\in\{L,N,Z\}}\frac{\partial y}{\partial X_i}\frac{\partial X_i}{\partial s}$ models how tractors indirectly impact production through the

[4] This framework is subject to the condition that the observed total horsepower should equal the actual horsepower utilized in the production function. However, due to the gap between the potential full capacity and the actual horsepower, the actual machinery input is unobserved in the data. Considering this practical constraint, we relax the assumption of M(s) and modify the theoretical framework as $Y = y(L, M, s, N, Z)$. The detailed illustration is in the Appendix 7.

mechanism of input-structure effect influenced intermediately by machinery structure.

In sum, the total effect of agricultural machinery on production can be decomposed into net direct effect ($\frac{\partial y}{\partial M}|_{s\ fixed}$) and machine-structure effect ($\frac{\partial s}{\partial M}(\frac{\partial y}{\partial s}+\sum_{i\in\{L,N,Z\}}\frac{\partial y}{\partial X_i}\frac{\partial X_i}{\partial s})$). Compared with Equation (2), it is obvious that $\frac{\partial y}{\partial M}=\frac{\partial y}{\partial M}|_{s\ fixed}+\frac{\partial s}{\partial M}\frac{\partial y}{\partial s}$ and $\sum_{i\in\{L,N,Z\}}\frac{\partial y}{\partial X_i}\frac{\partial X_i}{\partial M}=\frac{\partial s}{\partial M}\sum_{i\in\{L,N,Z\}}\frac{\partial y}{\partial X_i}\frac{\partial X_i}{\partial s}$, which represents the relationship between the original decomposition and the final form. Compared with previous studies, the derivation of theoretical models clarifies and interprets the direct and different structure effects of farming machines on total grain output.

To estimate the different structural effects of machinery via land, labor, and fertilizer on grain output empirically, we adopt the broadly used Translog production function which is regarded as a quadratic approximation to the unknown "true" function. There exist interactions of different inputs, providing an easy way to explore the input-structure effect in the basic function. Hence, the Translog production function can be written as:

$$\begin{aligned} lnY &= \beta_0 + \beta_L lnL + \beta_M lnM + \beta_N lnN + \beta_Z lnZ + \frac{1}{2}\beta_{LL}(lnL)^2 \\ &+\frac{1}{2}\beta_{MM}(lnM)^2 + \frac{1}{2}\beta_{NN}(lnN)^2 + \frac{1}{2}\beta_{ZZ}(lnZ)^2 \\ &+\beta_{LM} lnL\cdot lnM + \beta_{LN} lnL\cdot lnN + \beta_{LZ} lnL\cdot lnZ \\ &+\beta_{MN} lnM\cdot lnN + \beta_{MZ} lnM\cdot lnZ \\ &+\beta_{NZ} lnN\cdot lnZ \end{aligned} \tag{4}$$

In our empirical study, we insert the three-way continuous interaction of machinery structure *Struc*, machinery, and other inputs. To identify coefficients, we specify the function as follows:

$$\begin{aligned} ln\,y_{it} &= \alpha_0 + \sum_{j=1}^{4}\alpha_j lnx_{jit} + \frac{1}{2}\sum_{j=1}^{4}\alpha_{jj}(lnx_{jit})^2 \\ &+\sum_{j=1}^{3}\sum_{k\neq j}^{4}\alpha_{jk} lnx_{jit} lnx_{kit} + \delta_1 Struc_{it} + \delta_2 lnmach_{it} \\ &\times Struc_{it} + (\beta_1 lnland_{it} + \beta_2 lnlabor_{it} + \beta_3 lnferti_{it}) \\ &\times lnmach_{it}\times Struc_{it} + \gamma_1 AMPS_{it} + \gamma_2 AMPS_{it} \\ &\times lnmach_{it} + \gamma_3 AMPS_{it} \\ &\times Struc_{it} + \gamma_4 AMPS_{it} \\ &\times lnmach_{it}\times Struc_{it} + \theta_Z\cdot Z_{ijt} \\ &+u_i + \varepsilon_{it} \end{aligned} \tag{5}$$

where the dependent variable lny_{it} refers to the logarithm of agricultural production in county i at year t. lnx_{jit} and lnx_{kit} are different input factors, including machinery, land, labor, and fertilizer. $Struc_{it}$ refers to the proportion of the total power of large and medium-sized tractors. $AMPS_{it}$ is an indicator of the AMPS policy. For example, if the agricultural machinery purchasing subsidy is implemented in county i in year t, then $AMPS_{it}=1$ from year t; otherwise $AMPS_{it}=0$. $lnland_{it}$, $lnlabor_{it}$, $lnferti_{it}$, and $lnmach_{it}$ indicate the natural logarithms of four inputs in this study, which are land, labor, fertilizer, and machinery. Z_{ijt} is a set of control variables. u_i is the country fixed-effects, and ε_{it} is a random error following the normal distribution.

The parameter vector α indicates the coefficient of four inputs in the original Translog production function. The parameter vector δ refers to the net direct effect of the agricultural machinery on production. The parameter vector β refers to the interaction of the tractor power structure, farm machine, and other three inputs, which is the most important coefficient we care about. It captures the effects of machinery structural change. The parameter vector γ refers to the policy effect of government subsidy on purchasing farm machines, mainly reflected in the role of machinery input and the proportion of large and medium-sized tractors in agricultural production.

Although the fixed effect model helps to capture some individual-specific unobserved heterogeneities and alleviate the endogeneity, we also hope to capture both random and systematic inefficiencies that affect productivity. The production function is assumed to specify the feasible maximum output produced by a set of given inputs. Since output may not reach the frontier in reality, the stochastic frontier model was raised by Aigner et al. (1977) to describe technical inefficiency. The stochastic frontier approach (SFA) offers another perspective by quantifying the potential distance from the most efficient productivity. Therefore, we combine these two methods to understand the role of machinery structure in the agricultural productivity dynamics better. Greene (2005) and Yu (2012) proposed the true effects (TFE) model that allows fixed effects in time-varying models, hence this study follows the method, and the empirical model is specified as follows:

$$\begin{aligned} \ln y_{it} &= \alpha_i + \sum_{j=1}^{4}\alpha_j lnx_{jit} + \frac{1}{2}\sum_{j=1}^{4}\alpha_{jj}(lnx_{jit})^2 \\ &+\sum_{j=1}^{3}\sum_{k\neq j}^{4}\alpha_{jk} lnx_{jit} lnx_{kit} + \delta_1 Struc_{it} + \delta_2 lnmach_{it} \\ &\times Struc_{it} + (\beta_1 lnland_{it} + \beta_2 lnlabor_{it} + \beta_3 lnferti_{it}) \\ &\times lnmach_{it}\times Struc_{it} + \gamma_1 AMPS_{it} + \gamma_2 AMPS_{it} \end{aligned}$$

$$\times lnmach_{it} + \gamma_3 AMPS_{it}$$

$$\times Struc_{it} + \gamma_4 AMPS_{it} \times lnmach_{it}$$

$$\times Struc_{it} + \theta_Z \cdot Z_{ijt}$$

$$+ \varepsilon_{it} \tag{6}$$

$$\varepsilon_{it} = \upsilon_{it} - u_{it} \tag{7}$$

$$u_{it} = \delta(t)\, u_i \tag{8}$$

where $\upsilon_{it} \sim \mathcal{N}(0, \sigma_\upsilon^2)$, $u_i \sim Exp(\theta)$, υ_{it} and u_i are iid. The TFE model allows for the time-varying inefficiency term, as well as the individual fixed effect. Other variables and parameters are the same as those in the fixed effect model.

Furthermore, we discuss several issues related to multicollinearity and endogeneity to address the threat and ensure the validity of our results. The discussion of multicollinearity is reported in Appendix 1 in detail. We follow the methodology of Lin et al. (2022) and report normalized results of the estimation. Gong (2018) uses province-level panel data to estimate the production function and reviews the method to solve the endogeneity problem, in which all four inputs (labor, land, fertilizer, and machinery) are proved exogenous. Additionally, we refer to Amsler et al. (2016) and employ the control function method to solve the potential endogeneity problem of four inputs in Appendix 2. To address the endogeneity of machinery structure, we use the inverse-probability-weight methods (IPW, Horvitz & Thompson, 1952; Wooldridge, 2007). Further discussions are presented in Section 5.2.2.

4 | DATA

The empirical analysis in this study is based on a county-level dataset in Xinjiang and Hubei provinces during the period 2002–2012. In addition, we also collect partial data from Jilin province, therefore the results of the merged unbalanced panel will also be presented as a robustness check for supplementary. The main dataset comprises 126 counties in 26 prefectures, with a total of 1386 observations. The county-level data is collected from the *Chinese County Statistical Yearbook*, *Xinjiang Statistical Yearbook*, *Hubei Rural Statistical Yearbook*, and the Ministry of Agricultural and Rural Affairs of the People's Republic of China. The cost of crop input is collected from the *National Farm Product Cost-Benefit Survey*. The weather data is collected from the *China Meteorological Data Website*.

Hubei province is one of the major grain-producing areas and Xinjiang is famous for its agricultural modernization and mechanization. Hubei and Xinjiang possessed 1254 thousand and 677 thousand tractors respectively, ranking sixth and tenth in 2012. However, the internal structures of tractors' power capacity appear obvious differences in these provinces. From the perspective of the capacity of farm tractors, the share of large and medium factors surpassed 70% for Xinjiang in 2012, while the proportion for Hubei province is nearly 38%, and the total share in China is 45.25%. Similarly, the quantity shares of large and medium tractors are 51%, 11%, and 21% for Xinjiang, Hubei, and the whole country respectively. Due to data limitations regarding the machinery structure, our sample consists of two provinces in China. However, it's still reasonable and representative to utilize the county-level dataset. As a supplement, we construct a city-level dataset in Appendix 4, which includes 126 prefectures in 10 provinces from 2002 to 2012, providing additional evidence that supports the validity of our analysis and results.

The dependent variable in this study is total staple grain production, which includes rice, maize, wheat, other cereals, tuber crops, and soybeans.[5] The machinery input is defined as the total power capacity. The labor input is represented by the number of rural people employed in agriculture. The land acreage is defined as the sown area of grain, for it can measure the land input in production better. Meanwhile, the chemical fertilizer is converted to pure substance equivalent in the statistical yearbook in China. It should be noted that, given the widespread use of machinery in the grain production process, we use grain output as the key dependent variable. However, certain critical inputs used in the production function, such as labor and fertilizer, also encompass factors used in the cultivation of non-grain crops, owing to the absence of clear differentiation in factor inputs for different crops in the county-level statistics. To better understand the structure effects, we also show the results of several representative cash crops in Appendix 6.

The most important variable in the research is the agricultural machinery structure. Farming machines are classified into different types according to the food production process, including agricultural power machinery in all phases and other machines and tools related to each production phase. Tractors are the most common power machines and other specific machines contain soil tillage machinery, planting machinery, plant protection machinery, and crop harvesting machinery in the planting

[5] Precisely stated, the dependent variable should be defined as staple crop production since tuber crops and soybeans are both included in the statistics. Nevertheless, the National Bureau of Statistics of China officially defines this statistical variable as grain production. Hence, we adhere to this broader definition for consistency.

production. Since most specific farm tools and machines need to be used with tractors, the power capacity of tractors becomes a common indicator to measure the machinery size structure. In addition, the non-disclosure of detailed information on different types of supporting machines, and inconsistent disclosure types in each county make it impossible to measure the size structure of agricultural machinery by constructing other statistical variables. Therefore, our article uses the share of medium/large tractors' capacity to proxy the machinery size structure, the classification criteria of which have been introduced in Section 1. We also use the share of large/medium tractors' quantity in the further robustness check and use the share of supporting tools and machines for large/medium tractors in the supplementary prefecture-level dataset.

The construction of the policy indicator is based on the list of counties supported by the Agricultural Machinery Purchasing Subsides from 2004 to 2009, collected from the Ministry of Agricultural and Rural Affairs. The indicator of the subsidy is equal to 1 from the first year when the county was subsidized.

Control variables can be divided into three types. The first part is other inputs, including agrochemicals (pesticides and mulching film), seeds, mechanical hiring services, and irrigation. Among them, agrochemicals and seeds are aggregated into expenses as the mediate input. Apart from irrigated areas, other expenses are obtained by multiplying the input cost per mu of each province by the sown area as proxies. The second part is agroecological variables including average annual temperature and precipitation. The last type is the budget constraint used in the robustness check, including the proxy of deposit, loan, and agricultural GDP per capita.

There are also concerns about whether the machinery structures of the adjacent counties will affect agricultural production, especially due to the rapid development of agricultural mechanization outsourcing services. Firstly, the cross-regional services focus on harvesting across provinces, so the main machinery involved is the combine harvester rather than tractors (Zhang et al., 2017). As for four-wheel tractors, the maximum designed speed does not exceed 40 km/h, and tractors are prohibited on highways and roads in central urban areas of large and medium-sized cities. In our dataset, the average administrative area of Xinjiang's counties exceeds 20,000 square kilometers, thus tractors are hard to travel beyond the county boundaries. Secondly, the more common form of machinery hiring service is provided by specialized teams within villages, which are typically made up of several family members and equipped with large/medium tractors (Wang et al., 2016). Because of the above characteristics, the neighboring tractor sizes are omitted in the current control variables for simplification.

The descriptive statistics for all dependent and independent variables are displayed in Table 1.

5 | RESULTS AND DISCUSSIONS

5.1 | Impact of machinery capacity structure

5.1.1 | Conventional OLS regression

Table 2 represents the estimation of the production function in the fixed effect model. Column (1) reports the coefficients in the original Translog function, and controls other input factors, weather conditions, and county-fixed effects. Among the four major input factors, land affects production directly and is significant at 1% level. The key factor we focused on, machinery, has an indirect influence mainly through the sown area, significant at 1% level. Precisely, the rising use of machinery encourages farmers to increase sown area, thus improving grain production. Column (2) additionally reports the capacity structure effect of machinery on grain output compared with Column (1). Meanwhile, Column (3) reports the effect of the subsidy policy on total grain production. Columns (4) and (5) combine all the inputs, capacity structure interactions, machinery subsidy policy, and other control variables. The coefficients of three-way interactive terms between tractor size, machinery, and another input potentially reveal the existence of machinery capacity structure effect on grain production.

During the window period of the machinery subsidy, the structure of machinery capacity (represented by the capacity share of large tractors) mainly affects food output by readjusting fertilizer input in the production process. The land and labor channels are not significant in the fixed effect model. At the same time, the gradual implementation of the nationwide AMPS program could enhance grain production directly. Mathematically, after being supported by the AMPS program, the grain output in beneficiary prefectures will experience an approximately 20% increase. But there are also large negative effects of the subsidy policy through machinery structure change on grain output.

5.1.2 | Stochastic frontier analysis

This subsection will display the estimated results of the SFA analysis. The prerequisite to applying the stochastic frontier model is the existence of the inefficiency term. After the likelihood-ratio test of the original Translog production function, it is reported that the null hypothesis is

TABLE 1 Summary statistics.

Variable	Definition	Mean	S.D.	Xinjiang Mean	Xinjiang S.D.	Hubei Mean	Hubei S.D.
Panel A: Dependent variable							
lny	Total grain output (10^4 ton)	2.457	1.124	1.969	1.142	3.174	.584
lny_ha	Grain output per hectare (ton/ha)	1.746	.304	1.789	.271	1.681	.338
lncotton	Total output of cotton (10^4 ton)	−.373	1.570	−.048	1.499	−.851	1.551
lnoil	Total output of oil plants (10^4 ton)	−.505	1.734	−1.387	1.602	.792	.909
lncashcrop	Total output of cotton and oil plants (10^4 ton)	.372	1.351	.034	1.464	.869	.972
Panel B: Main input factors							
lnmach	Machinery total capacity (10^4 kw)	2.552	.846	2.227	.808	3.030	.652
lnlabor	Rural population employed in agricultural sector (10^4 units)	1.687	.893	1.193	.785	2.414	.423
lnland	Grain sown area (10^3 ha)	3.014	1.077	2.483	1.049	3.795	.473
lnferti	Use of chemical fertilizers (ton)	9.333	1.315	8.749	1.293	10.19	.759
lnland_cash	Sown area of cash crop (10^3 ha)	3.010	.869	2.708	.900	3.454	.587
Panel C: Other input factors							
lnmaterial	Total cost of other agricultural materials, including pesticide, seeds and agricultural film (10^4 yuan)	7.731	1.108	7.269	1.130	8.412	.614
lnservice	Cost of agricultural machinery service (10^4 yuan)	7.255	1.098	7.058	1.179	7.544	.893
lninput	Total cost of agricultural materials and machinery service (10^4 yuan)	8.235	1.083	7.865	1.151	8.779	.673
lnirr	Effective irrigated area (10^3 ha)	3.049	.865	3.156	.831	2.891	.889
Panel D: Machinery structure							
Struc_kw	Share of large/medium tractors for the total capacity	.542	.203	.508	.160	.592	.246
Struc_q	Share of large/medium tractors for the total quantity	.357	.220	.321	.173	.408	.266
Panel E: Subsidy policy							
AMPS	=1 since the county is supported by AMPS subsidy; = 0 if not subsidized	.630	.483	.635	.482	.622	.485
Panel F: Weather condition							
temperature	Average annual temperature (°C)	12.321	4.038	9.318	2.186	16.737	.682
lnrainfall	Average annual precipitation (mm)	8.369	.850	7.712	.354	9.336	.176
Panel G: Budget constraint							
lnagrincome	Agricultural income per capita (yuan)	4.913	.719	4.992	.762	4.797	.634
lnsavings	Household savings balance (10^4 yuan)	7.121	1.254	6.550	1.191	7.958	.786
lndebt	Balance of loans (10^4 yuan)	6.844	1.238	6.370	1.284	7.538	.745
Observations		1386 (100%)		825 (59.5%)		561 (40.5%)	

Note: The table summarizes all the variables in the baseline regression and robustness check. All the inputs and outputs are in the form of a logarithm. Large/medium tractors refer to tractors with power capacity over 14.74 kW (20 horsepower), among which large tractors are over 36.78 kW (50 horsepower) and medium tractors lay between 20 and 50 horsepower. All the variables related to the cost have been adjusted by the price index.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

TABLE 2 Fixed effect estimation.

Variables	(1) Original production function	(2) Add machinery structure	(3) Add AMPS policy	(4) Baseline	(5) Aggregating other control inputs
lnmach	.042	−.151	.114	−.109	−.063
	(.218)	(.227)	(.214)	(.227)	(.226)
lnland	1.008***	1.028***	1.082***	1.090***	1.057***
	(.281)	(.285)	(.269)	(.282)	(.283)
lnlabor	−.294	−.261	−.257	−.260	−.257
	(.341)	(.313)	(.311)	(.293)	(.293)
lnferti	.201	.157	.147	.118	.103
	(.150)	(.131)	(.159)	(.146)	(.146)
lnmach×lnmach	−.036	−.024	−.048*	−.037	−.036
	(.023)	(.024)	(.025)	(.027)	(.027)
lnland×lnland	.021	.010	.021	.009	.008
	(.016)	(.015)	(.015)	(.015)	(.015)
lnlabor×lnlabor	.114**	.106**	.117**	.106**	.103**
	(.051)	(.051)	(.052)	(.051)	(.050)
lnferti×lnferti	−.008	−.005	−.004	−.002	−.001
	(.013)	(.012)	(.013)	(.012)	(.012)
lnmach×lnland	.207***	.160***	.210***	.166***	.167***
	(.046)	(.052)	(.046)	(.053)	(.054)
lnmach×lnlabor	−.098*	−.124**	−.112**	−.119**	−.107*
	(.053)	(.053)	(.054)	(.054)	(.054)
lnmach×lnferti	−.038	−.010	−.039	−.012	−.018
	(.028)	(.029)	(.028)	(.029)	(.029)
lnland×lnlabor	−.315***	−.291***	−.319***	−.295***	−.296***
	(.066)	(.062)	(.066)	(.063)	(.062)
lnland×lnferti	−.048	−.044	−.052	−.048	−.046
	(.040)	(.040)	(.039)	(.040)	(.040)
lnlabor×lnferti	.129***	.126***	.129***	.127***	.123***
	(.048)	(.045)	(.045)	(.042)	(.043)
Struc_kw		−.336*		−.266	−.287
		(.173)		(.199)	(.201)
Struc_kw×lnmach		.445		.439	.426
		(.289)		(.288)	(.288)
Struc_kw×lnmach×lnland		.064		.062	.060
		(.050)		(.050)	(.051)
Struc_kw×lnmach×lnlabor		.007		.001	.003
		(.045)		(.045)	(.045)
Struc_kw×lnmach×lnferti		−.057**		−.055**	−.054**
		(.025)		(.025)	(.025)
AMPS			.257**	.191*	.134
			(.100)	(.110)	(.112)
AMPS×lnmach			−.065*	−.035	−.020
			(.035)	(.039)	(.040)
AMPS×Struc_kw			−.504***	−.353*	−.276
			(.179)	(.212)	(.216)

(Continues)

TABLE 2 (Continued)

Variables	(1) Original production function	(2) Add machinery structure	(3) Add AMPS policy	(4) Baseline	(5) Aggregating other control inputs
AMPS×lnmach×Struc_kw			.156**	.087	.072
			(.062)	(.076)	(.077)
lnirr	.082***	.080**	.073**	.074**	.068**
	(.031)	(.032)	(.032)	(.034)	(.034)
lnmaterial	−.002	−.001	−.031	−.033	
	(.027)	(.027)	(.024)	(.024)	
lnservice	.066***	.067***	.069***	.074***	
	(.022)	(.021)	(.022)	(.022)	
lninput					.061**
					(.031)
Constant	−3.468***	−3.310***	−3.133***	−2.963***	−3.099***
	(.626)	(.577)	(.652)	(.592)	(.601)
County FE	YES	YES	YES	YES	YES
Weather condition variables	YES	YES	YES	YES	YES
R-square	.821	.824	.824	.826	.825
Observations	1386	1386	1386	1386	1386

Note: The dependent variable is total grain output, and the explanatory variables sequentially consist of main input factors, capacity structure proxies, and the policy indicator. Columns (4) and (5) include all these explanatory variables. All regressions control county fixed effects, and also control other input and weather condition variables. The variable *lninput* represents the total cost of agricultural materials and machinery service. The robust standard errors are all clustered at the county level. Robust standard errors are in parentheses with *** denoting significance at 1%, ** at 5%, and * at 10%.

rejected, which means it's reasonable to apply SFA. The estimated results are reported in Table 3.

The regression order in Table 3 is consistent with Table 2 for the sake of comparison. The estimated coefficients of our interest in the regression remain similar, and the machinery structure effect through the land channel is significant in the SFA model. The results indicate that a higher input of large/medium tractors can strengthen the influence of machinery on grain output through two channels, the positive mechanism in land and the negative mechanism in fertilizer. This is consistent with the economic intuition we discussed in the background section, as the introduction of more large machinery encourages farmers to expand production scale. The negative mechanisms are dominant in the structure effects through the fertilizer channel. Meanwhile, the effects of subsidies on grain output are also consistent with previous results. The AMPS program not only directly affects production, but also indirectly affects grain production through the interaction with agricultural machinery and the power structure of machinery.

FE model and TFE model both confirm the existence of a capacity structure effect of agricultural machinery on grain production, with different channels displaying opposite effects. The TFE model is not only a robustness check but also captures how the combination of input factors produces the maximum possible output and identifies the technical efficiency compared to the FE model. And we will further discuss how technical efficiency changes with subsidy policies and the scale of machinery capacity based on the SFA method in the later section. Next, we will decompose and calculate various structure effects of machinery.

5.1.3 | Structure effects and misallocation

In Section 3, the theoretical models show that $\frac{\partial s}{\partial M}(\frac{\partial y}{\partial s}+\sum_{i\in\{L,N,Z\}}\frac{\partial y}{\partial X_i}\frac{\partial X_i}{\partial s})$ presents the capacity structure effect of agricultural machinery on total grain output. We consequently calculate the marginal effects of machinery and the capacity structure effects in grain production estimated by the TFE model. Using the coefficients displayed in Column (5) in Table 3 and mean values of key input factors in the overall sample and subsamples, we decompose the structure effects of machinery into the direct channel and three input factor channels, and mainly focus on land and fertilizer channels. Table 4 reports the average marginal effects and capacity structure effects of agricultural machinery in total and for different provinces. The estimated structure effects are components

TABLE 3 Stochastic frontier estimation.

Variables	(1) Original production function	(2) Add machinery structure	(3) Add AMPS policy	(4) Baseline	(5) Aggregating other control inputs
lnmach	.225	.055	.375*	.185	.237
	(.189)	(.207)	(.213)	(.225)	(.215)
lnmach×lnmach	−.016	−.000	−.032	−.020	−.022
	(.025)	(.029)	(.029)	(.032)	(.030)
lnmach×lnland	.213***	.160***	.214***	.165***	.170***
	(.057)	(.060)	(.056)	(.061)	(.060)
lnmach×lnlabor	−.155**	−.155**	−.167***	−.149**	−.134**
	(.065)	(.066)	(.063)	(.067)	(.067)
lnmach×lnferti	−.055**	−.035	−.062**	−.043	−.050*
	(.026)	(.027)	(.029)	(.030)	(.029)
Struc_kw		−.315		−.193	−.227
		(.192)		(.212)	(.214)
Struc_kw×lnmach		.372		.362	.365
		(.282)		(.270)	(.275)
Struc_kw×lnmach×lnland		.079*		.079*	.073*
		(.046)		(.043)	(.044)
Struc_kw×lnmach×lnlabor		−.040		−.047	−.044
		(.047)		(.044)	(.044)
Struc_kw×lnmach×lnferti		−.045*		−.044**	−.043*
		(.023)		(.022)	(.023)
AMPS			.233**	.204*	.161
			(.100)	(.112)	(.114)
AMPS×lnmach			−.060*	−.040	−.029
			(.034)	(.040)	(.041)
AMPS×Struc_kw			−.560***	−.490**	−.439*
			(.190)	(.220)	(.225)
AMPS×lnmach×Struc_kw			.178***	.132*	.125
			(.064)	(.078)	(.080)
lnirr	.097**	.086**	.082**	.075**	.068*
	(.039)	(.039)	(.037)	(.037)	(.037)
lnmaterial	.008	.013	−.001	.002	
	(.027)	(.028)	(.028)	(.029)	
lnservice	.075***	.075***	.073***	.083***	
	(.020)	(.020)	(.021)	(.020)	
lninput					.096***
					(.031)
County FE	YES	YES	YES	YES	YES
Weather condition variables	YES	YES	YES	YES	YES
Wald chi-square	1699.42	2027.82	1929.56	2505.69	2540.23
σ_u	.105	.106	.107	.108	.110
σ_v	.077	.075	.073	.070	.071
λ	1.366	1.413	1.454	1.556	1.559
Observations	1386	1386	1386	1386	1386

(Continues)

TABLE 3 (Continued)

Note: The dependent variable is total grain output, and the explanatory variables sequentially consist of main input factors, capacity structure proxies and the policy indicator. Columns (4) and (5) include all these explanatory variables. All regressions control county fixed effects, and also control other input and weather condition variables. The variable *lninput* represents the total cost of agricultural materials and machinery service. Other independent variables are not displayed due to the limited space. $\lambda = \sigma_u/\sigma_v$. The robust standard errors are all clustered at the county level and are in parentheses with *** denoting significance at 1%, ** at 5%, and * at 10%.

of the average marginal effects of agricultural machinery on production.

It is observed that the positive direct effect and structure effect dominate in the full sample, resulting in a positive overall effect[6]. Even though the total structure effect of farming machines on grain output is not significantly positive, capacity structure effects are observed significantly in the form of readjustment of land and fertilizer factors. When the input of machinery increases by 10%, grain production will increase by about 1.19% through a positive land channel of structure effect. Conversely, a 10% growth in the input of agricultural machines also will reduce grain output by nearly 2.20% due to the adverse impact of fertilizer reduction.

The decomposition of overall effects displays a heterogeneous pattern in subsamples. The total effect and direct effect are both positive in Xinjiang, but the total effect has almost disappeared in Hubei because of the smaller direct effect compared to Xinjiang. However, the land and fertilizer channel of the capacity structure in Hubei is significantly larger. The disparities between the two groups may be attributed to the fact that Hubei is a traditional major grain-producing area with labor-intensive smallholders. With the limitation of land fragmentation, the direct effect of agricultural machinery on production is smaller. However, there still exists ample opportunity to restructure the land factor through collective large-scale social services.

Some studies suggest that the impact of agricultural machinery on food security is relatively small compared to other factors like land, labor, and fertilizer (Ji et al., 2012). This article shows that only focusing on the total marginal effect of the machinery is far from enough, the leverage effect of machinery on grain production should not be ignored. Different from other inputs, agricultural machines are production tools with properties of both capital investment and technology, which do not directly convert to the energy that plants need to grow. This characteristic of agricultural machinery determines the way it affects agricultural production. Previous literature has mainly focused on the direct influence of machines in the production function, ignoring the indirect and structure effects of agricultural machinery as advances in technology through other input channels. On the one hand, with the popularization and use of agricultural machinery, grain harvest areas will gradually expand through land integration and social service, thus promoting food production. On the other hand, large-scale agricultural machines are usually operated by professional operators and cooperatives, and they can also promote planting grain crops that need less fertilizer. These mechanisms systematically reduce the input of fertilizer, further decreasing food production. The results of this study show that the promotion of the structure effect via the land channel is smaller than the inhibition via the fertilizer channel. While the positive direct channel (*Struc_kw*×*lnmach*) offsets the negative effects. The overall structure effect is therefore numerically small, which may explain the reason why studies always underestimate the influence of agricultural machinery on food production.

We then calculate the average marginal effects of capacity structure varying with the sown area of grain, as displayed in Figure 2. Besides the average marginal effects, there is also a kernel density curve of land input shown in this figure. The major y-axis represents kernel density while the marginal effects are on the minor y-axis. We find the average marginal effects of capacity structure change from negative to positive as the sown area grows, with the turning point between $lnland = 3$ and $lnland = 4$. The results make intuitive sense, as large tractors are more productive when the land input is larger due to the economies of scale. Conversely, if the arable land is inadequate, large machines cannot be used at maximum efficiency. The marginal effect is slightly negative at the average value of the sown area, indicating that the structure misallocation of agricultural machinery hinders the potential influence of farming machines on food security. The findings complement the results of Foster and Rosenzweig (2022). Following their theory of the U-shaped relationship between farm scale and productivity, government programs like the AMPS policy aim to promote high-capacity machines to increase farm productivity, but insufficient land leads to large-scale agricultural machinery not reaching its production potential.

5.1.4 | Robustness check

Our robustness checks of this study include replacing important variables, changing the setup of empirical models, and using the alternative unbalanced panel data, respectively shown in Tables A6–A8 in Appendix 5. Instead

[6] The output elasticities of all factors are reported in Appendix 3. The contribution to grain production is land, labor, machinery, and fertilizer in descending order.

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The Journal of the International Association of Agricultural Economists

TABLE 4 The marginal effects of agricultural machinery.

	Total		Xinjiang		Hubei	
marginal effects	**Estimation**	**S.E.**	**Estimation**	**S.E.**	**Estimation**	**S.E.**
Panel A: Marginal effects of machinery and decomposition						
Total effect	.0305	(.037)	.0506	(.049)	.0009	(.036)
Direct effect	.1240	(.288)	.1385	(.275)	.1028	(.309)
Indirect effect	−.1778	(.283)	−.1732	(.266)	−.1845	(.310)
Structure effect	.0577	(.053)	.0582	(.055)	.0561	(.051)
Panel B: Decomposition of power capacity structure effect						
Direct channel	.1981	(.149)	.1856	(.140)	.2165	(.163)
Land channel	.1194*	(.072)	.0922*	(.055)	.1643*	(.099)
Labor channel	−.0399	(.040)	−.0265	(.027)	−.0624	(.063)
Fertilizer channel	−.2199*	(.114)	−.1931*	(.100)	−.2623*	(.137)

Note: The capacity structure effects of machinery are calculated according to the TFE model as follows: $(\delta_2 + \beta_1\overline{lnland} + \beta_2\overline{lnlabor} + \beta_3\overline{lnferti}) \times \overline{Struc}$ where $\overline{lnland}$, $\overline{lnlabor}$, $\overline{lnferti}$ and $\overline{Struc}$ are the mean of input factors and capacity structure. The structure effects of Xinjiang and Hubei are based on the mean value of these two provinces respectively. Standard errors are shown in parentheses with *** denoting significance at 1%, ** at 5%, and * at 10%.

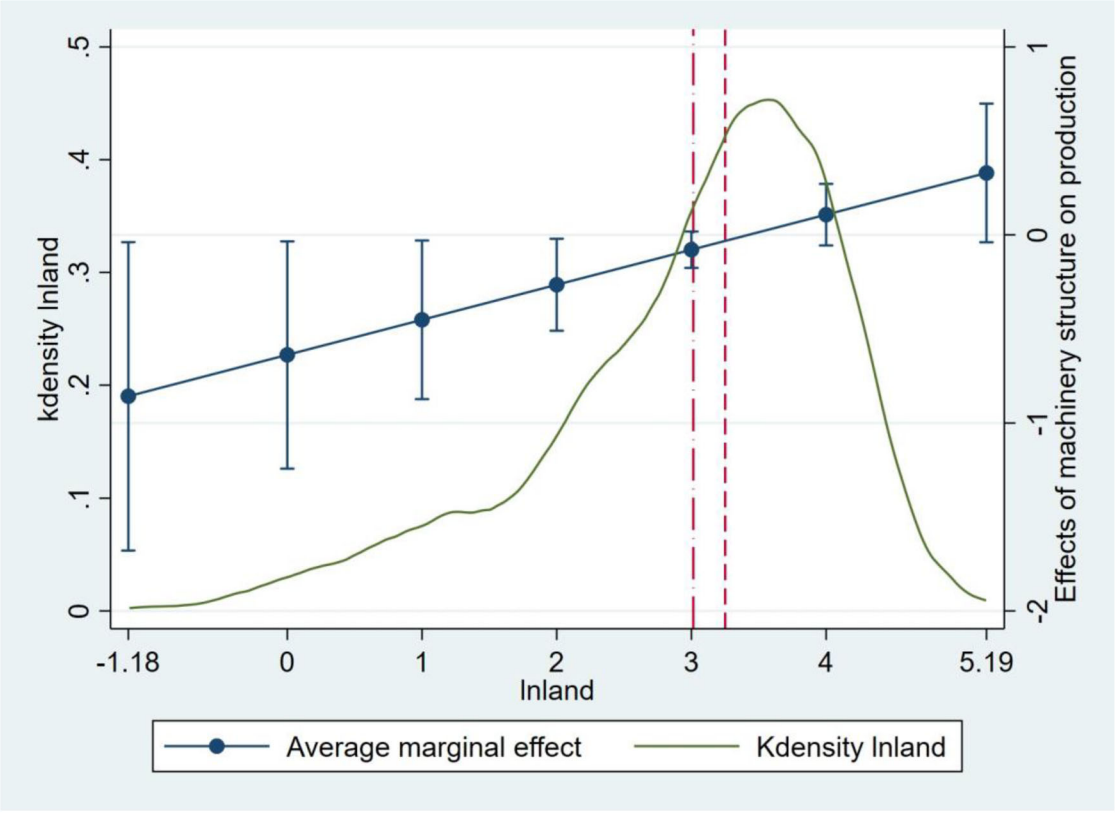

FIGURE 2 Average marginal effects of machinery structure varying with sown land area.

Note: The figure shows how average marginal effects of machinery structure (*Struckw*) vary with *lnland*. The density of *lnland* is labeled in the major y-axis, and the average marginal effects of *Struckw* are labeled in the minor y-axis. The effects are shown with 90% confidence intervals. The vertical dash-dot line shows the mean of *lnland* (mean = 3.014) and the next dash line points to the median of *lnland* (median = 3.250). The average marginal effects are calculated according to the results of the true fixed effect (TFE) model and the kernel density estimation is based on the Epanechnikov kernel function. The marginal effects and kernel density are estimated using balanced panel data of Xinjiang and Hubei from 2002 to 2012.

of capacity share, we use the quantity proportion of large and medium-sized tractors as the proxy to measure agricultural machinery structure. We also use arable land area instead of planting acreage of grain crops. The grain sown area calculates actual planting acreage of multiple cropping while arable land area is a stock. Both of the measurements are widely used in estimating the production function empirically. Furthermore, we use grain output per hectare instead of total grain output to capture the effect. For alternative setups of the empirical models, our study changes the distribution of the inefficiency term in the TFE model. We also use the random-effects time-varying efficiency decay model (RE) and the Iterative Least Squares time-varying fixed-effects model (FELS) to check the robustness. Since the farmers' decisions on the usage of tractors and other inputs allocation are influenced by budget constraints, we add savings, loans, and agricultural GDP per capita in rural areas to control variables based on the TFE model. The main coefficients are generally robust, while the land channel is less stable than the fertilizer channel.

As mentioned in Section 4, we also report the results of the unbalanced panel data. The results remain robust when measuring the tractor size based on horsepower. However, when measuring the tractor size based on quantity, only the structure effect in fertilizer is still robust. In this circumstance, the tractor size positively affects the direct machinery channel, rather than the joint machinery-land channel.

5.2 | Further discussion

5.2.1 | Alternative specification and model validity

In the basic regressions, we use the Translog production function to match the theoretical model. As aforementioned, this framework is subject to the condition that the observed total horsepower should equal the actual horsepower utilized in the production function. However, the actual machinery input is unobserved in the data because of the gap between the potential full capacity and the actual horsepower. Therefore, we further relax the assumption of M(s) and modify the theoretical framework as $Y = y(L,M,s,N,Z)$. A more detailed demonstration is in Appendix 7. To fit the less constrained framework, we provide empirical results of alternative production function forms including both the Cobb-Douglas function and Translog function where machinery structure is embedded like an input factor rather than a moderator. Figure 3 plots the key coefficients related to machinery structure in different models and the corresponding estimations are in Tables A10 and A11. In the simplified setup, the structure effects comprise a direct effect on output and indirect effects, where the latter manifest as interaction terms between machinery structure and input factors. The direct effect of the tractor scale is neither significant in the baseline nor robust, but the positive indirect effects via the land channel and negative indirect effects via the fertilizer channel are strongly robust.[7]

As the empirical model contains both the production and AMPS policy components, we also check if our production function estimation is reasonable by separately estimating these two parts and deducing the output effect. Appendix 7 illustrates the method and estimation. We back out the effects of AMPS on total output and find it is consistent with the direct estimated effect. Theoretically, the Frisch–Waugh–Lovell Theorem emphasizes the equivalence of the coefficients from both full and partial regressions. Solid evidence shows that our production function model is valid.

5.2.2 | Endogeneity of machinery structure

Given that agricultural machinery structure is the focal variable in this article, special attention has been directed towards the endogeneity issue associated with it. The tractor scale might be influenced by changes in input endowments, and the measurement error can also introduce endogeneity. Therefore, we use the aforementioned IPW method to address this concern. With reference to Takeshima (2017), the machinery structure is converted to binary variables by using the median as the threshold. After conducting the Probit regression on the machinery power structure in the first stage, the IPW method assigns weights and adjusts for the unequal probability of each individual receiving the treatment, thus reducing the estimation bias. By utilizing the R package in machine learning, we have also provided estimation results when treating machinery structure as the continuous dependent variable in the first stage. Table 5 summarizes the estimated coefficients through the IPW-OLS method, differentiated by the tractor scale status.

In general, the results adjusted by the IPW method remain consistent compared with the baseline, as shown in Column (3). Nonetheless, the results exhibit highly interesting heterogeneities between the high share of large/medium tractors and the low share group in

[7] In addition, Cobb–Douglas function form also help to explore structure effects interacting with more other inputs. The expansion of large/medium tractors indirectly promotes grain output by expanding the irrigation area and also generates negative indirect effects by reducing the marginal impact of agricultural machinery outsourcing services.

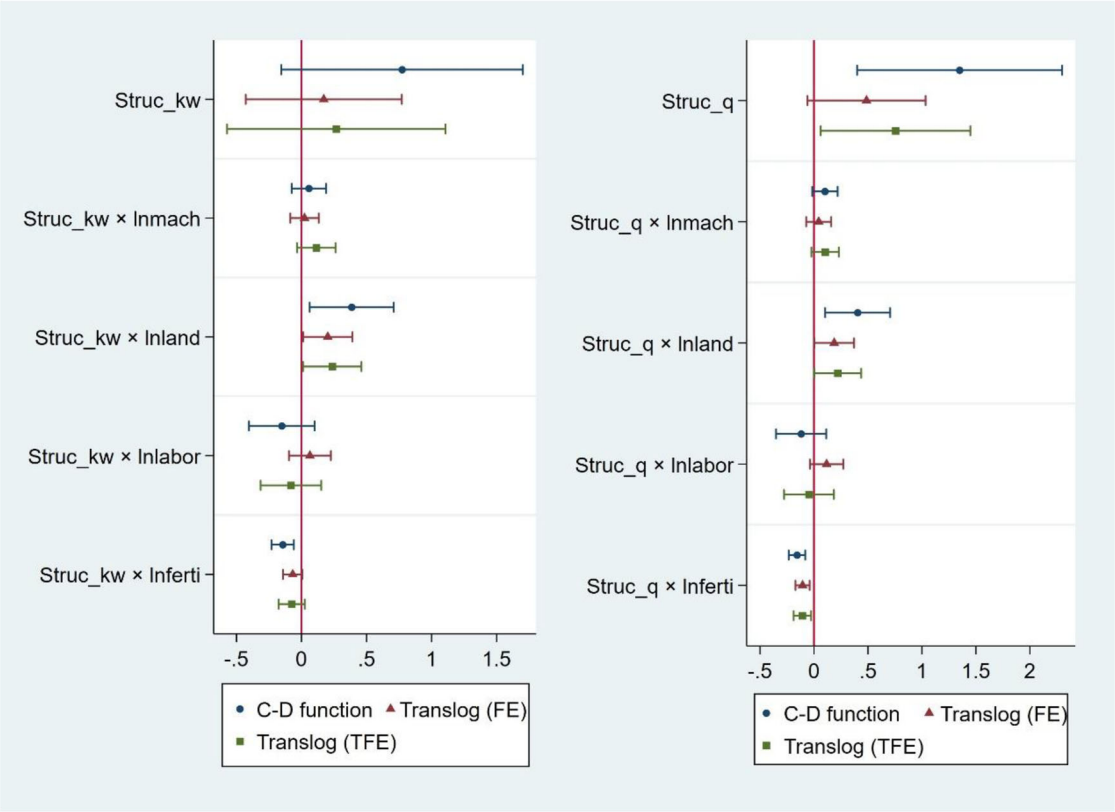

FIGURE 3 Structure effects in different alternative models. This figure presents the main coefficients related to machinery structure in the Cobb–Douglas production function, Translog production function with fixed effects, and Translog production function with true fixed effects, respectively. The machinery structure is proxied by the horsepower capacity share in the left figure, and the dependent variable is the total grain output. The corresponding results are in Column (1) of Table A10 and Columns (2) and (5) of Table A11. Similarly, the machinery structure in the right figure is measured by quantity share, and the dependent variable is the grain output per hectare. The corresponding results are in Column (3) of Table A10 and Columns (3) and (6) of Table A11.

Columns (1) and (2). In the low proportion group, the increased adoption of large tractors significantly promotes the joint effect of machinery and land on grain output. While the coefficient of the fertilizer channel turns out to be significantly positive. When the adoption of large/medium tractors is low, the growth of large tractors has a direct promoting effect on grain output, but also weakens the direct marginal effect of machinery on production. Conversely, in the high proportion group, the sustained growth of large machines leads to a direct decline in grain production, yet amplifies the direct marginal effect of machinery. The promotion of machinery structure also results in a lower joint effect of machinery and fertilizer on production.

The heterogeneous results illustrate the marginal effect of introducing large tractors mainly reflects on expanding cultivated area and promoting complementarity between machinery and fertilizer when there are fewer high-capacity tractors. Nonetheless, in scenarios where high-capacity machines are more prevalent, the marginal effect is no longer reflected in the land expansion channel. Instead, the negative structure effects through the fertilizer channel are dominant due to fertilizer saving and grain crop changes. Since recent mechanization literature delves into focus on the farming systems and mechanization typology issues, our findings enrich the literature, and the heterogeneity of farming systems may need more in-depth research in future studies (Takeshima et al., 2013; Warren, 2023).

5.2.3 | Subsidy policy effect

To investigate the impact of the AMPS policy through various input factors on grain production, we extend the subsidy policy effects by introducing interaction terms between policy indicator and input factors, using both Cobb–Douglas and Translog specifications. The estimation results are summarized in Table 6. After being supported by the subsidy policy, the positive effects of land and

TABLE 5 Results estimated by IPW method.

	Low-share group	High-share group	Continuous Structure
	(1)	(2)	(3)
Variables	**Total output**	**Total output**	**Total output**
Struc	1.008**	−.983**	−.111
	(.426)	(.408)	(.155)
Struc×lnmach	−1.330***	1.439***	.380**
	(.487)	(.438)	(.173)
Struc×lnmach×lnland	.134**	.034	.048**
	(.057)	(.048)	(.023)
Struc×lnmach×lnlabor	−.104	.013	.021
	(.064)	(.055)	(.020)
Struc×lnmach×lnferti	.088*	−.127***	−.054***
	(.047)	(.039)	(.016)
AMPS	−.066	.430	.130**
	(.175)	(.292)	(.062)
AMPS×lnmach	.062	−.140	−.026
	(.064)	(.115)	(.024)
AMPS×Struc	.154	−.728*	−.346**
	(.425)	(.439)	(.152)
AMPS×lnmach×Struc	−.139	.241	.109**
	(.163)	(.168)	(.054)
County FE	YES	YES	YES
Other input variables	YES	YES	YES
Weather condition variables	YES	YES	YES
Budget constraints variables	YES	YES	YES
R-square	.836	.738	.821
Observations	693	691	1384

Note: The low-share group in Column (1) refers to the group with a proportion of large/medium tractors below the median, while the high-share group in Column (2) refers to those above the median. The weights of the first two columns are estimated by the Probit model, while the weight of Column (3) is estimated by the generalized linear model (GLM). The robust standard errors are all clustered at the county level and are in parentheses with *** denoting significance at 1%, ** at 5%, and * at 10%.

outsourcing services on grain output are significantly strengthened. However, the subsidy has also significantly weakened the role of labor, chemical fertilizer, and other agricultural material inputs in production.[8] The coefficients of the major input factors are also consistent in the Translog specification.

Furthermore, to avoid the potential estimation biases in the traditional Difference-in-Difference (DID) model, we simply use the Local Projection Difference-in-Differences (LP-DID) approach to check the robustness of the results and also capture the potential dynamic responses to the policy change over time (Dube et al., 2023). The treatment effects are estimated using three different LP-DID methods based on the simplified Cobb–Douglas specification and are depicted in Figure 4. It illustrates that the AMPS policy has a lag effect on production. It takes approximately 2 years for the subsidy to significantly show a directly positive influence on grain output.

5.2.4 | Technical efficiency pattern

Based on the Translog SFA, we estimate the technical efficiency for every county each year. Figure 5 depicts the distribution of estimated TE and the time trend. With consideration of capacity and subsidy policy, the mean technical efficiency is .883, shown in Panel A of Table 7. Our estimations of technical efficiency are comparable with those in the literature (Tian & Wan, 2000).

In Table 7, we also simply summarize the mean of TE under various situations. Panel B reports the average

[8] The effects of AMPS policy on different input factors are also demonstrated in Table A12 of Appendix 7.

TABLE 6 AMPS policy effect.

	C-D	C-D	Translog FE	Translog FE	Translog TFE	Translog TFE
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Total output**	**Total output**	**Total output**	**Yield**	**Yield**	**Total output**
AMPS	1.372**	1.414**	−.149	−.149	.014	−.025
	(.559)	(.560)	(.200)	(.200)	(.186)	(.165)
AMPS×Struc	.044	.020	−.069	−.069	−.342*	−.457**
	(.080)	(.078)	(.229)	(.229)	(.207)	(.221)
AMPS×lnmach	−.042	−.043	−.014	−.014	−.059	−.062**
	(.030)	(.029)	(.047)	(.047)	(.042)	(.030)
AMPS×lnland	.461***	.464***	.173***	.173***	.178***	.176***
	(.122)	(.123)	(.029)	(.029)	(.039)	(.034)
AMPS×lnlabor	−.155***	−.154***	−.153***	−.153***	−.145***	−.149***
	(.043)	(.044)	(.036)	(.036)	(.035)	(.034)
AMPS×lnferti	−.037*	−.041*	−.007	−.007	−.005	−.002
	(.021)	(.021)	(.024)	(.024)	(.022)	(.021)
AMPS×lnmaterial	−.533***	−.524***				
	(.177)	(.183)				
AMPS×lnservice	.277***	.265***				
	(.091)	(.093)				
AMPS×lnirr	.000	.005				
	(.024)	(.023)				
AMPS×lnmach×Struc			−.006	−.006	.075	.120
			(.080)	(.080)	(.075)	(.080)
Constant	−1.077	−.889	−.053	2.249***	-	-
	(.915)	(.840)	(.860)	(.860)	-	-
Other input variables	YES	YES	YES	YES	YES	YES
Weather condition	YES	YES	YES	YES	YES	YES
Poor×Year FE	YES	YES	YES	YES	NO	NO
HBP×Year FE	YES	YES	YES	YES	NO	NO
County FE	YES	YES	YES	YES	YES	YES
R-square	.755	.757	.792	.365	-	-
Wald chi-square	-	-	-	-	429.88	3375.59
Observations	1386	1386	1386	1386	1386	1386

Note: Results in Columns (1) and (2) are based on the Cobb-Douglas production function, and results in Columns (3) to (6) are based on the Translog production function. The machinery structures in Columns (2) and (6) are calculated by the quantity, and others are calculated by the horsepower. The robust standard errors are all clustered at the county level and are in parentheses with *** denoting significance at 1%, ** at 5%, and * at 10%.

TE before and after the subsidy policy, while Panel C represents how means of TE vary across five quantiles of agricultural machinery capacity structure. The results reveal a heterogeneous pattern of technical efficiency across different quantiles of machinery capacity structure. On average, the larger estimations of TE are observed in Quantile 1 and Quantile 4. Quantile 1 has an average share of large and medium-sized tractors of 26.71%. The high technical efficiency may be attributed to intensive cultivation using small tractors. The next peak level appears in Quantile 4 either on average (capacity structure ranges from 58.95% to 72.95%) or in Xinjiang (53.81%–64.62%), whereas in Hubei province, the highest value is shown in Quantile 3 (55.66%–65.90%). High TE does not always correspond to high mechanization symbolled by the proportion of large and medium-sized tractors. The matching pattern between agricultural machinery and farming conditions plays an essential role. When the share of large tractors exceeds a certain threshold, the technical efficiency will go into reverse. This phenomenon implies that agricultural modernization should not blindly pursue the scale of machinery, but should adjust according to local endowments, considering both production and efficiency.

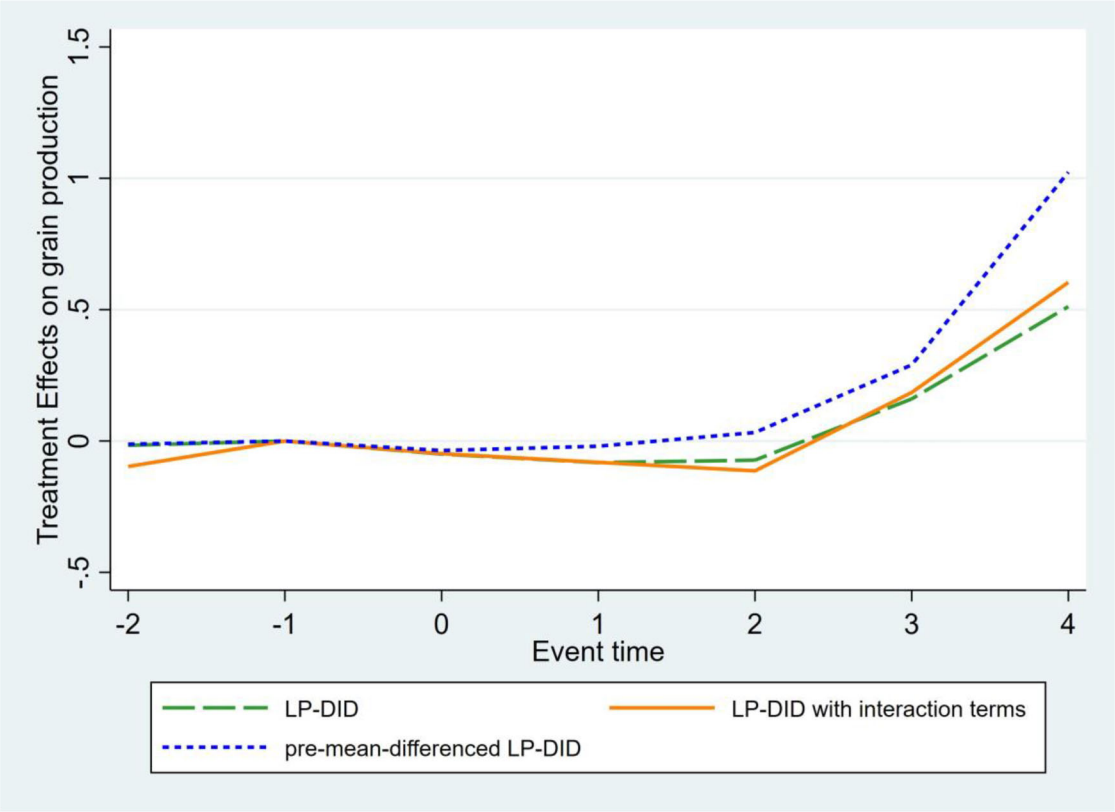

FIGURE 4 Treatment effects of the AMPS policy estimated by LP-DID method.

Note: The figure illustrates the treatment effects of the Agricultural Machinery Purchase Subsidies (AMPS) on grain production over time which are estimated by the Local Projection Difference-in-Differences (LP-DID) model using the county-level dataset of Xinjiang and Hubei from 2002 to 2012. The horizontal axis represents the periods before and after the first implementation of the AMPS policy. These three treatment effects are estimated by the basic LP-DID, LP-DID with interaction terms, and pre-mean-differenced LP-DID.

TABLE 7 Summary statistics of technical efficiency.

	Total		Xinjiang		Hubei	
Category	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Panel A: Overall						
Technical efficiency	.8827	.070	.8825	.074	.8830	.065
Panel B: Policy implementation						
Before subsidy	.8815	.045	.8832	.048	.8792	.041
After subsidy	.8833	.030	.8820	.030	.8853	.029
Panel C: Quantiles of capacity structure						
Quantile 1	.8864	.057	.8870	.060	.8839	.054
Quantile 2	.8750	.078	.8746	.075	.8841	.072
Quantile 3	.8840	.076	.8794	.089	.8874	.063
Quantile 4	.8920	.056	.8895	.058	.8854	.057
Quantile 5	.8759	.080	.8817	.082	.8742	.076

Note: For simplicity and intuition, the technical efficiency is calculated on the foundation of the basic TFE model without other control variables, where the inefficiency term follows the prevailing half-normal distribution. We create five quantiles to capture the difference in technical efficiency when the share of large and medium-sized tractors changes. Quantiles of two subsamples are recreated within each group. The means of capacity structure for five quantiles in the overall dataset are .27, .42, .53, .66, and .84; for Xinjiang, the means of each quantile are .30, .41, .50, .58, .75; for Hubei, the means are .22, .44, .63, .76, and .91, respectively.

FIGURE 5 Time trend of technical efficiency in Xinjiang and Hubei from 2002 to 2012.

Note: The figure shows the technical efficiency (TE) of different counties in the dataset in Xinjiang and Hubei from 2002 to 2012. TE is estimated by the stochastic frontier analysis (SFA) and represented by the scatters. The boxplot displays the TE distribution in each year and the mean TE is labeled as well.

6 | CONCLUSION AND POLICY IMPLICATIONS

Given that agricultural modernization and food security are always the top priorities in developing countries, this article investigates how agricultural machinery affects grain production, with a particular emphasis on its capacity structure effect and the role of subsidy policy. We present the empirical study by constructing a panel dataset of China's counties in Xinjiang and Hubei provinces from 2002 to 2012, covering the period in which the subsidy policy was gradually promoted, and estimating the results through the fixed effect model and SFA.

The main finding is that the total machinery capacity can increase grain output, and the structure of machinery also matters. The general elasticity of output with respect to machinery inputs is .03. The capacity structure effect of agricultural machinery contributes to grain production by readjusting land and fertilizer input in the production process. The diffusion of larger tractors significantly improves crop sown area and reduces fertilizer use, thus jointly resulting in variation in food output. When the input of machinery increases by 10%, grain production will increase by about 1.19% through a positive land channel of structure effect. In contrast, a 10% growth in the input of agricultural machines also will reduce grain output by nearly 2.20% due to the adverse impact of fertilizer reduction. The average marginal effects of machinery structure turn from negative to positive with increasing sown area, but the effects remain mostly negative given the land scale in our sample.

The structural misallocation of agricultural machinery hinders the potential influence of farming machines on food security. Our results also indicate that the AMPS policy helps directly increase the grain output, while it has a lag effect and it takes two years to show a significantly positive direct effect due to the temporal hysteresis. Furthermore, we estimate the technical efficiency of each county based on the SFA model. Simple descriptive statistics display that the mean value of TE is .883 and estimations between different quantiles of machinery capacity structure are heterogeneous.

Our results are robust when controlling for various fixed effects, changing measurements of variables, and adjusting the SFA model. Other doubts about multicollinearity, endogeneity, and sample selection are all discussed as far as possible. After adjusting for the endogeneity issue of machinery structure using the IPW method, we find that the land channel of the structure effect primarily exists in the group with a lower proportion of large/medium tractors. Meanwhile, the structure effect in the fertilizer channel is negative in the high share group, but turns to positive in the low proportion group. We also construct

a prefecture-level and unbalanced panel dataset, trying to find solid empirical evidence for our theory of the mechanical structure effect through different factor channels. Moreover, we also relax the assumption and compare structure effects among different alternative function specifications. Solid evidence verifies the validity of our model and the robustness of the results.

This article distinguishes between the direct effect, indirect effect, and capacity structure effect of machinery on grain output in the Translog production function theoretically. These findings contribute to a more comprehensive understanding of how the scale of agricultural machinery impacts productivity. Even though the article only consists of two provinces as representation on account of the limitation of power capacity structure in different counties, all of the above analyses support that the power capacity structure of farming machines should be carefully considered by the government when establishing subsidy policies to promote the diffusion of agricultural machinery. The average size of tractors in China is still smaller than those in developed countries like America, so current government subsidies in China tend toward larger machines. However, more utilization of large-sized tractors does not always guarantee higher outputs, because the matching pattern between agricultural machinery and farming conditions matters, concerning both grain production and efficiency. Our results suggest that investments in modernized mechanization in production tend to be meaningful in fighting against starvation, addressing food insecurity, and promoting sustainable agricultural development, primarily due to the leverage impact of machinery capacity structure. Our findings may apply to developing countries whose grain production is dominant and arable land is scarce and fragmental. As a policy recommendation for countries with limited land endowment, agricultural modernization should not blindly pursue the scale of machinery. The experience and conclusions in China have strong policy implications for other developing countries on the road to agricultural modernization, but the findings may not be readily extended to countries with considerably different characteristics from those in this study.

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REFERENCES

Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21–37. https://doi.org/10.1016/0304-4076(77)90052-5

Amsler, C., Prokhorov, A., & Schmidt, P. (2016). Endogeneity in stochastic frontier models. *Journal of Econometrics*, *190*(2), 280–288. https://doi.org/10.1016/j.jeconom.2015.06.013

Baudron, F., Sims, B., Justice, S., Kahan, D. G., Rose, R., Mkomwa, S., Kaumbutho, P., Sariah, J., Nazare, R., Moges, G., & Gérard, B. (2015). Re-examining appropriate mechanization in Eastern and Southern Africa: Two-wheel tractors, conservation agriculture, and private sector involvement. *Food Security*, *7*(4), 889–904. https://doi.org/10.1007/s12571-015-0476-3

Benin, S. (2015). Impact of Ghana's agricultural mechanization services center program. *Agricultural Economics*, *46*(S1), 103–117. https://doi.org/10.1111/agec.12201

Binswanger, H. (1986). Agricultural mechanization: A comparative historical perspective. World Bank Research Observer, *1*.

Bravo-Ureta, B. E., Higgins, D., & Arslan, A. (2020). Irrigation infrastructure and farm productivity in the Philippines: A stochastic meta-frontier analysis. *World Development*, *135*, 105073. https://doi.org/10.1016/j.worlddev.2020.105073

Chen, Q. (2014). *Advanced econometrics and application in Stata* (Vol. 183). Higher Education Press.

Chen, S., & Lan, X. (2020). Tractor vs. animal: Rural reforms and technology adoption in China. *Journal of Development Economics*, *147*, 102536. https://doi.org/10.1016/j.jdeveco.2020.102536

Cochrane, W. W. (1958). *Farm prices: Myth and reality*. U of Minnesota Press.

Daum, T. (2023). Mechanization and sustainable agri-food system transformation in the Global South. A review. *Agronomy for Sustainable Development*, *43*(1), 16. https://doi.org/10.1007/s13593-023-00868-x

Diao, X., Takeshima, H., & Zhang, X. (2020). *An evolving paradigm of agricultural mechanization development: How much can Africa learn from Asia?* International Food Policy Research Institute (IFPRI). https://doi.org/10.2499/9780896293809

Dube, A., Girardi, D., Jordà, Ò., & Taylor, A. M. (2023). *A local projections approach to difference-in-differences event studies* (Working Paper 31184). National Bureau of Economic Research. https://doi.org/10.3386/w31184

FAO (Food and Agriculture Organization of the United Nations). (2022). The state of food and agriculture 2022. *Leveraging automation in agriculture for transforming agrifood systems*. FAO. https://doi.org/10.4060/cb9479en

Foster, A. D., & Rosenzweig, M. R. (2022). Are there too many farms in the world? Labor market transaction costs, machine capacities, and optimal farm size. *Journal of Political Economy*, *130*(3), 636–680. https://doi.org/10.1086/717890

Gong, B. (2018). Agricultural reforms and production in China: Changes in provincial production function and productivity in 1978–2015. *Journal of Development Economics*, *132*, 18–31. https://doi.org/10.1016/j.jdeveco.2017.12.005

Greene, W. (2005). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis*, *23*(1), 7–32. https://doi.org/10.1007/s11123-004-8545-1

Hayami, Y., & Ruttan, V. W. (1970). Agricultural productivity differences among countries. *American Economic Review*, *60*(5), 895–911. https://www.jstor.org/stable/1818289

He, C., Ho, C. Y., Yu, L., & Zhu, X. (2019). Public investment and food security: Evidence from the Hundred Billion Plan in China. *China Economic Review*, *54*, 176-190. https://doi.org/10.1016/j.chieco.2018.11.002

Hicks, J. (1963). *The theory of wages*. Springer.

Horvitz, D. G., & Thompson, D. J. (1952). A generalization of sampling without replacement from a Finite Universe. *Journal of the American Statistical Association*, *47*(260), 663–685. https://doi.org/10.1080/01621459.1952.10483446

Huang, J., Wang, X., & Rozelle, S. (2013). The subsidization of farming households in China's agriculture. *Food Policy*, *41*, 124–132. https://doi.org/10.1016/j.foodpol.2013.04.011

Hume, D. (1907). *Essays moral, political, and literary* (Vol. 1). Longmans, Green, and Company.

Jetté-Nantel, S., Hu, W., & Liu, Y. (2020). Economies of scale and mechanization in Chinese corn and wheat production. *Applied Economics*, *52*(25), 2751–2765. https://doi.org/10.1080/00036846.2019.1696933

Ji, Y., Yu, X., & Zhong, F. (2012). Machinery investment decision and off-farm employment in rural China. *China Economic Review*, *23*(1), 71–80. https://doi.org/10.1016/j.chieco.2011.08.001

Kahan, D., Bymolt, R., & Zaal, F. (2018). Thinking outside the plot: Insights on small-scale mechanisation from case studies in East Africa. *The Journal of Development Studies*, *54*(11), 1939–1954. https://doi.org/10.1080/00220388.2017.1329525

Lin, B., Wang, X., Jin, S., Yang, W., & Li, H. (2022). Impacts of cooperative membership on rice productivity: Evidence from China. *World Development*, *150*, 105669. https://doi.org/10.1016/j.worlddev.2021.105669

Lin, W., & Huang, J. (2021). Impacts of agricultural incentive policies on land rental prices: New evidence from China. *Food Policy*, *104*, 102125. https://doi.org/10.1016/j.foodpol.2021.102125

Lu, Q., Du, X., & Qiu, H. (2022). Adoption patterns and productivity impacts of agricultural mechanization services. *Agricultural Economics*, *53*(5), 826–845. https://doi.org/10.1111/agec.12737

Liu, Y., Hu, W., Jetté-Nantel, S., & Tian, Z. (2014). The influence of labor price change on agricultural machinery usage in Chinese agriculture. *Canadian Journal of Agricultural Economics/Revue Canadienne Dägroeconomie*, *62*(2), 219–243. https://doi.org/10.1111/cjag.12024

Ma, W., Zhu, Z., & Zhou, X. (2021). Agricultural mechanization and cropland abandonment in rural China. *Applied Economics Letters*, 526–533. https://doi.org/10.1080/13504851.2021.1875113

McArthur, J. W., & McCord, G. C. (2017). Fertilizing growth: Agricultural inputs and their effects in economic development. *Journal of Development Economics*, *127*, 133–152. https://doi.org/10.1016/j.jdeveco.2017.02.007

Otsuka, K. (2013). Food insecurity, income inequality, and the changing comparative advantage in world agriculture. *Agricultural Economics*, *44*(s1), 7–18. https://doi.org/10.1111/agec.12046

Qian, L., Lu, H., Gao, Q., & Lu, H. (2022). Household-owned farm machinery vs. Outsourced machinery services: The impact of agricultural mechanization on the land leasing behavior of relatively large-scale farmers in China. *Land Use Policy*, *115*, 106008. https://doi.org/10.1016/j.landusepol.2022.106008

Qing, Y., Chen, M., Sheng, Y., & Huang, J. (2019). Mechanization services, farm productivity and institutional innovation in China. *China Agricultural Economic Review*, *11*(3), 536–554. https://doi.org/10.1108/CAER-12-2018-0244

Ruttan, V. W., & Hayami, Y. (1971). *Agricultural development: An international perspective*. Johns Hopkins Press.

Schultz, T. W. (1964). *Transforming traditional agriculture* (Vol. 212). Yale University Press.

Smale, M., Assima, A., Kergna, A., Thériault, V., & Weltzien, E. (2018). Farm family effects of adopting improved and hybrid sorghum seed in the Sudan Savanna of West Africa. *Food Policy*, *74*, 162–171. https://doi.org/10.1016/j.foodpol.2018.01.001

Sun, F., Abler, D., & Yu, X. (2021). Crop allocation and increasing returns to fertilizer use in China. *Land Economics*, *97*(2), 491–508. https://doi.org/10.3368/le.97.2.491

Takeshima, H. (2017). Custom-hired tractor services and returns to scale in smallholder agriculture: A production function approach. *Agricultural Economics*, *48*(3), 363–372. https://doi.org/10.1111/agec.12339

Takeshima, H., Hatzenbuehler, P. L., & Hyacinth, O. E. (2020). Effects of agricultural mechanization on economies of scope in crop production in Nigeria. *Agricultural Systems*, *177*, 102691. https://doi.org/10.1016/j.agsy.2019.102691

Takeshima, H., Nin-Pratt, A., & Diao, X. (2013). Mechanization and agricultural technology evolution, agricultural intensification in Sub-Saharan Africa: Typology of agricultural mechanization in Nigeria. *American Journal of Agricultural Economics*, *95*(5), 1230–1236. https://www.jstor.org/stable/24476904

Tian, W., & Wan, G. H. (2000). Technical efficiency and its determinants in China's grain production. *Journal of Productivity Analysis*, *13*(2), 159–174. https://doi.org/10.1023/A:1007805015716

Tian, X., Yi, F., & Yu, X. (2020). Rising cost of labor and transformations in grain production in China. *China Agricultural Economic Review*, *12*(1), 158–172. https://doi.org/10.1108/CAER-04-2018-0067

USDA. (2019). Census of agriculture. *United States Department of Agriculture*. http://www.agcensus.usda.gov/

Wang, X., Yamauchi, F., Otsuka, K., & Huang, J. (2016). Wage growth, landholding, and mechanization in Chinese agriculture. *World Development*, *86*, 30–45. https://doi.org/10.1016/j.worlddev.2016.05.002

Warren, F. (2023). Population density, urbanisation and agricultural mechanisation in modern Ghana. *Review of Development Economics*, *27*(3), 1605–1629. https://doi.org/10.1111/rode.13007

Wooldridge, J. M. (2007). Inverse probability weighted estimation for general missing data problems. *Journal of Econometrics*, *141*(2), 1281–1301. https://doi.org/10.1016/j.jeconom.2007.02.002

Yang, J., Huang, Z., Zhang, X., & Reardon, T. (2013). The rapid rise of cross-regional agricultural mechanization services in China. *American Journal of Agricultural Economics*, *95*(5), 1245–1251. https://www.jstor.org/stable/24476906

Yi, F., Sun, D., & Zhou, Y. (2015). Grain subsidy, liquidity constraints and food security—Impact of the grain subsidy program on the grain-sown areas in China. *Food Policy*, *50*, 114–124. https://doi.org/10.1016/j.foodpol.2014.10.009

Yi, Q., Chen, M., Sheng, Y., & Huang, J. (2019). Mechanization services, farm productivity and institutional innovation in China. *China Agricultural Economic Review*, *11*(3), 536–554. https://doi.org/10.1108/caer-12-2018-0244

Yu, X. (2012). Productivity, efficiency and structural problems in Chinese dairy farms. *China Agricultural Economic Review*, *4*(2), 168–175. https://doi.org/10.1108/17561371211224755

Zhang, W., Zheng, C., Song, Z., Deng, A., & He, Z. (2015). Chapter 3 - Farming systems in China: Innovations for sustainable crop production. In V. O. Sadras & D. F. Calderini (Eds.), *Crop physiology* (2nd ed., pp. 43–64). Academic Press. https://doi.org/10.1016/B978-0-12-417104-6.00003-0

Zhang, X., Hu, L., & Yu, X. (2023). Farmland leasing, misallocation reduction, and agricultural total factor productivity: Insights from rice production in China. *Food Policy*, *119*, 102518. https://doi.org/10.1016/j.foodpol.2023.102518

Zhang, X., Yang, J., & Thomas, R. (2017). Mechanization outsourcing clusters and division of labor in Chinese agriculture. *China Economic Review*, *43*, 184–195. https://doi.org/10.1016/j.chieco.2017.01.012

Zhang, X., Yu, X., & You, L. (2020). Does the Granary County Subsidy Program Lead to manipulation of grain production data in China? *China Economic Review*, *62*, 101347. https://doi.org/10.1016/j.chieco.2019.101347

Zhong, X., Zhou, S., & Yu, X. (2023). Land market misallocation, regional integration, and economic growth: Evidence from the Yangtze River Delta Region, China. *Public Administration and Development*, 1–15. https://doi.org/10.1002/pad.2033

Zou, B., Mishra, A. K., & Luo, B. (2020). Grain subsidy, off-farm labor supply and farmland leasing: Evidence from China. *China Economic Review*, *62*, 101293. https://doi.org/10.1016/j.chieco.2019.04.001

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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