https://doi.org/10.17221/291/2023-AGRICECON

Mechanisation's impact on agricultural total factor productivity

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Citation: Cui Y.X. (2023): Mechanisation's impact on agricultural total factor productivity. Agric. Econ. – Czech, 69: 446–457.

Abstract: Agricultural mechanisation is rapidly increasing in China and will have an increasing impact on agricultural total factor productivity (*TFP*) in the future. This study uses panel data from 27 provinces in China, spanning the years 2001–2020, to measure agricultural *TFP*, and estimates the effects of mechanisation on *TFP*, technical efficiency, and technological progress. The results reveal that the level of agricultural mechanisation can promote *TFP*. *TFP* has a cumulative effect in the previous period, which can also significantly affect *TFP* in the current period. The level of agricultural mechanisation improves technical efficiency and promotes technological progress, but this is not statistically significant. Regional heterogeneity exists in mechanisation's effect on agricultural *TFP*, with the largest effect occurring in the group with the lowest *TFP*. Therefore, efforts to promote the use of agricultural machinery should increase. China's agricultural machinery subsidy policy must be further adjusted, and agricultural machinery research investments increased, while the government must address the heterogeneity between regions and focus on developing agricultural mechanisation in the central and western regions.

Keywords: agriculture; agricultural development; machine; rate of production; technical efficiency; technological progress

Chinese agriculture is dominated by an intensive 'smallholder' farming production method, and many scholars have argued that the traditional smallholder attributes of Chinese agriculture, land fragmentation, and large losses in the labour force will reduce agricultural output (Rahman and Rahman 2008; Manjunatha et al. 2013; Tan et al. 2020). However, as per the National Bureau of Statistics of China, the agricultural labour force in the past two decades has declined, from 360 million in 2000 to 170 million in 2021; the total agricultural output value has increased from 20.38 billion USD to 114.64 billion USD; and the unit areas of production for such major crops as rice, corn, and wheat have increased by 12.56%, 37.40%, and 50.62%, respectively, between 2000 and 2019. This creates a paradox in which the farm output steadily increased over time, despite China's small farms and large labour exodus (Zhang et al. 2017).

It is widely believed that mechanisation has been the most important reason for China's steadily growing agricultural production over the past two decades, despite small farms, high land fragmentation, and rising wages (Yang et al. 2013; Wang et al. 2016; Abay et al. 2019). With industrialisation and urbanisation, the transfer of rural labour to both cities and non-agricultural sectors has accelerated. A consequence of ur-

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ban migration is that farmers have begun to purchase many general-purpose machines for self-use, joint use, or customised use (Shi et al. 2021). According to the National Bureau of Statistics of China, the number of small tractors in China decreased between 1978 to 2021 from 1.773 million to 1.675 million, and the number of medium-sized and large tractors increased from 0.557 million to 4.98 million. By 2021, the total output value of China's agricultural machinery industry was estimated to exceed 68.99 billion USD, and the number of enterprises in the agricultural machinery and equipment industry will exceed 8 000, meeting 90% of domestic market demand.

In response to this growth, China has focused on the nationwide development of agricultural mechanisation; in 2020, the central government's 'Document No. 1' proposed to improve the agricultural production service system for small farmers. The 20th National Congress of the Communist Party of China emphasised 'strengthening agricultural science and technology and equipment support'. On March 28, 2023, the Ministry of Agriculture and Rural Affairs aimed to 'accelerate the full and high-quality development of agricultural mechanisation, to provide strong mechanisation support to ensure a stable and safe supply of food and important agricultural products, comprehensively promote the revitalisation of the countryside, and accelerate the construction of a strong agricultural country'.

Hence, the development of agricultural mechanisation must assess agricultural mechanisation's impact on agricultural total factor productivity (*TFP*). Similar to the agricultural development history of other countries worldwide, China faces a decreased agricultural labour force and limited arable land area. Improving agricultural *TFP* is the only way to guarantee long-term agricultural stability. In the context of China's rural revitalisation strategy, the nation has especially focused on improving *TFP*, and improving the agricultural *TFP* in particular is the primary issue in building a strong agricultural country. General Secretary Xi Jinping said: 'We should give more prominence to improving the comprehensive production capacity of agriculture and improving the level of agricultural equipment'.

China's 1979 rural reform and opening-up policy led to a massive migration of rural labour to cities. The new economics of labour mobility (Stark and Bloom 1985) argue that labour migration tends to be substituted and invested in agricultural production through capital factors, such as fertiliser and machinery, to compensate for the losses due to labour shortages. This implies that agricultural machinery is a labour input (Qiao 2017) and an important substitute for agricultural labour. Moreover, Zhang et al. (2017) argued that agricultural mechanisation is an important reason for the steady growth of agricultural production, given China's declining agricultural labour. Mechanisation is the most profitable and contributes the most to growth where land is abundant, labour is scarce relative to land, and labour is rapidly leaving the land (Binswanger 1986).

Literature on mechanisation includes two main categories of research (Qiao 2017; Shi et al. 2021; Daum 2023). First, mechanisation is important in transforming agricultural development. As mechanised harvesting directly depends on labour costs, it is rarely profitable in low-wage countries. The more intense an operation's controls, the greater the labour cost that must be expended to use a machine (Binswanger 1986). In low-wage economies, only a few machines are economically viable in a given region (Jayasuriya et al. 1986), implying that mechanisation correlates with labour income levels, increases as labour income levels increase, and its development can also lead to higher labour income levels. Daum (2023) argued that mechanisation as an innovation is important for agro-sustainable development. Agricultural mechanisation makes agro-food systems more sustainable in terms of labour productivity, poverty reduction, food security, health, well-being, and other economic and social aspects. In the past half-century, developing regions have adopted labour-saving technologies at unprecedented levels, except sub-Saharan Africa (Pingali 2020). Economic growth and the commercialisation of agricultural systems have also led to the further mechanisation of agricultural systems in Asia and Latin America.

The second category of mechanisation research involves the mechanisation level's impact on agricultural production. The United Kingdom's Parliamentary Office of Science and Technology (2006) argues that decreasing poverty and increasing food security require a coordinated drive across industrial sectors, with the foremost being increasing the level of agricultural *TFP*; hence, the literature examined the determination and impact of farmers' adoption of non-mechanised, semi-mechanised, and integrated mechanised farming techniques on land productivity.

The replacement of traditional factors with modern agricultural production factors is an inevitable result of agricultural modernisation. However, Shi et al. (2021) observed that machine use had a limited impact on agricultural output; mechanisation and customised

https://doi.org/10.17221/291/2023-AGRICECON

services were primarily used to replace labour and were unlikely to increase yields. Qiao (2017) analysed mechanisation's effects on the areas sown for different crops and revealed that mechanisation positively affected food (grain) crops and negatively affected non-grain crops while reducing diversity.

These studies focused on three aspects: agricultural mechanisation's importance in the agricultural development process, the relationship between agricultural mechanisation and the labour force, and agricultural mechanisation's impact on single-crop production. This study contributes to existing literature in several ways. First, it further decomposes agricultural *TFP* into technical efficiency and technical progress indexes to clarify the mechanism by which agricultural mechanisation impacts *TFP*. Second, it considers the differences in agricultural *TFP* across China and groups 27 provinces according to the size of their agricultural *TFP*. In doing so, the study tests the regional heterogeneity of the agricultural mechanisation level's impact on *TFP* in China. Third, considering the lags and interactions of variables, first-order lag terms of agricultural *TFP*, and levels of economic development and financial support, the model setting introduces interaction terms for the infrastructure and mechanisation levels, and interaction terms for financial support and the mechanisation level.

This study selected 540 observations from 27 provinces spanning 2001–2020 and compiled panel data based on the results. We then analysed whether the agricultural mechanisation level could contribute to improving *TFP* and its path of influence and conducted a regional heterogeneity analysis. Our main finding is that the level of agricultural mechanisation can promote *TFP*; simultaneously, *TFP* has a cumulative effect: *TFP* in the previous period can also significantly affect *TFP* in the current period. The agricultural mechanisation level had the largest effect on the nine provinces, with the lowest *TFP* in agriculture but the level of agricultural mechanisation had the largest effect on technical efficiency in the nine provinces with the highest *TFP* in agriculture.

MATERIAL AND METHODS

Total factor productivity measurement and decomposition in agriculture. According to Solow's economic growth model, the *TFP* is the residual part of economic growth after excluding such factor inputs as labour, capital, and natural resources. Aigner et al. (1977) further decomposed *TFP* into frontier technical progress and technical efficiency. To measure *TFP*, we adopted a nonparametric approach that considers the DEA-based Malmquist index constructed by Färe et al. (1994) and others, calculated as follows [Equation (1)]:

$$M_i\left(x^{t+1},y^{t+1},x^t,y^t\right)=\frac{D_i^{t+1}\left(x^{t+1},y^{t+1}\right)}{D_i^t\left(x^t,y^t\right)}\times$$
$$\times\left[\frac{D_i^t\left(x^{t+1},y^{t+1}\right)}{D_i^{t+1}\left(x^{t+1},y^{t+1}\right)}\times\frac{D_i^t\left(x^t,y^t\right)}{D_i^{t+1}\left(x^t,y^t\right)}\right]^{\frac{1}{2}}= \quad (1)$$
$$=EC\times TC=EC\times PE\times SE$$

where: M – Malmquist productivity index; D – distance function; EC – technical efficiency; TC – technical progress, which can be further decomposed into PE (an index of the change in technical efficiency) and SE (an index of the change in scale efficiency); i – region; t – time; x – input sets of each period; y – output sets of each period.

This study takes each province in China as a decision unit, and the input–output data for agriculture in 27 provinces from 2001 to 2020 were selected to calculate agricultural *TFP*. The total agricultural output value was deflated as the output indicator, with 2000 used as the base period. The input indicators included labour, land, biochemical materials, and agricultural machinery material inputs. The number of employees in the primary industry represents the labour input index, in which the missing values are filled by linear interpolation. The total sown area of crops represents the land input index. The sum of plastic film, pesticide, and chemical fertiliser usage was used to measure the biochemical information input indicators. The total power of agricultural machinery indicates the input index for the agricultural machinery information.

This study measured the agricultural *TFP* in 27 provinces from 2001 to 2020 according to Equation (1) and then decomposed the technical efficiency and technical progress indexes. At the national level, agricultural *TFP* scored less than 1 in 2009 and more than 1 in all other years, indicating an overall upward trend in Chinese agriculture from 2001 to 2020. As illustrated in Figure 1, the technical efficiency and technical progress indexes for Chinese agriculture fluctuated around 1 and increased and decreased, respectively; in 2020, the increase in the technological progress index also increased the agricultural *TFP*.

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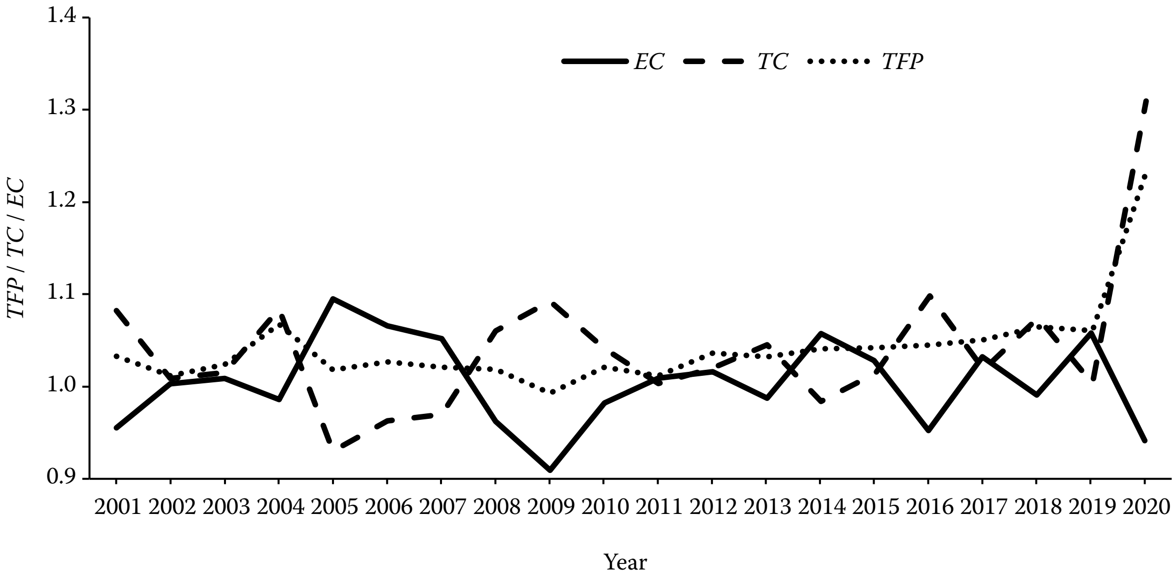

Figure 1. Trends of total factor productivity (*TFP*), technical progress (*TC*), and technical efficiency (*EC*) in China's agriculture (2001–2020)

Source: Own processing based on National Bureau of Statistic (2002–2021a, c, d)

Data selection and sources. This study's core explanatory variable was the comprehensive operational level of agricultural mechanisation (*MEC*). We selected the sum of the proportions of the machine ploughing, machine sowing, electromechanical irrigation, mechanical plant protection, and machine harvesting areas as the comprehensive index to measure the level of agricultural mechanisation operations according to each link in the agricultural production chain. The calculation method was as follows: comprehensive operational level of agricultural mechanisation = proportion of machine ploughing area × 0.22 + proportion of machine sowing area × 0.2 + proportion of electromechanical irrigation area × 0.22 + proportion of machine planting area × 0.18+ proportion of machine harvesting area × 0.18. The calculation reveals that from 2000 to 2020 the comprehensive operation level of China's agricultural mechanisation rose from 25.94% to 50.58%, and the five provinces with the fastest growth rates were Guizhou, Guangxi, Hainan, Yunnan, and Jiangxi. By 2020, the overall employment levels of agricultural mechanisation in Heilongjiang, Jiangsu, Anhui, Hebei, and Shandong were the highest at 79.23%, 77.01%, 69.17%, 67.80%, and 67.19%, respectively. The overall employment level of agricultural mechanisation in Yunnan, Guizhou, Chongqing, Hainan, and Sichuan was the lowest (20.01%, 20.63%, 29.73%, 31.64%, and 32.23%, respectively), and the gap between the levels of agricultural mechanisation in each region expanded, from 50.25% in 2000 to 59.22% in 2020. Overall, China's agricultural mechanisation was still at a low development level, and the variability among regions is gradually expanding.

Additionally, the levels of economic development (*ECO*), financial support (*FIN*), education (*EDU*), and infrastructure (*ELE*), as well as the disaster rate (*DIS*), were selected as control variables. Specifically:

i) The regional economic development level was expressed as rural *per capita* disposable income, and the factor inputs correlate with labour income levels. The higher the rural *per capita* income level, the more likely it will increase factor inputs and improve agricultural *TFP*.

ii) The intensity of financial support was expressed as each region's total agricultural expenditures. The period from 2007 to 2020 was selected to represent the intensity of financial support from local financial expenditures for agriculture, forestry, and water affairs; 2003 to 2006 was selected to represent the sum of agricultural expenditures, forestry expenditures, and business expenses for each region's agriculture, forestry, water conservancy, and meteorology departments. Moreover, 2000 to 2002 was selected to represent the intensity of financial support by using the expenditures that supported rural production from 2000 to 2002. This also included expenditures for comprehensive agricultural development and business expenses from the agriculture, forestry, water conservancy, and meteorology departments.

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iii) The disaster rate was calculated as the ratio of disaster areas to affected areas in each province. The higher the disaster rate, the more vulnerable the province to extreme disasters, indicating that the province had a large disaster area or poor resilience to risk, leading to lower yields and factor productivity.

iv) Regarding the infrastructure level, the mechanisation of power-intensive operations is well developed throughout Asia (Pingali 2007). The mechanisation of power-intensive processing and pumping operations always precedes the mechanisation of harvesting and planting operations and can be profitable at low wages (Binswanger 1986). Therefore, rural electricity consumption was used as an indicator of infrastructure development.

v) Education was expressed as the average number of years of education in the villages in each province. The higher the rural residents' educational level, the more likely they will use higher-quality, more efficient production factors and increase *TFP*.

Studies have measured labour force quality primarily from a human capital perspective by using the average years of schooling as an indicator (Barron 1993). Therefore, this study calculated the educational level as follows: the average years of education = (number of people with no schooling × 0 + number of people with primary schooling × 6 + number of people with junior high schooling × 9 + number of people with senior high schooling × 12 + number of people with senior high schooling or higher × 15) / total number of people.

This study selected 540 observations from 27 provinces from 2001 to 2020 to establish its panel data, including the National Statistical Yearbook, China Labour Statistical Yearbook, China Rural Statistical Yearbook, China Population and Employment Statistical Yearbook, China Agricultural Machinery Industry Yearbook, and Provincial Statistical Yearbooks (China Machinery Industry Information Research Institute et al. 2002–2021; National Bureau of Statistic 2002–2021a, b, c, d, e). Table 1 presents the variables' descriptive statistics.

Table 1. Descriptive statistics of the variables of interest (540 observations)

Variable	Mean	SD.	Min.	Max.
TFP	1.0450	0.0827	0.5060	1.7050
EC	1.0083	0.1114	0.6930	2.4990
TC	1.0442	0.1081	0.3840	1.5580
MEC	0.3763	0.1812	0.0247	0.7923
ECO	7 689.4260	5 125.7870	1 446.0000	31 930.0000
DIS	0.4977	0.1345	0.1482	0.8777
FIN	338.5055	309.4500	5.5353	1 339.3600
ELE	228.4956	355.2441	1.8000	2 011.0000
EDU	7.3468	0.6857	4.8148	8.9097

TFP – total factor productivity; *EC* – technical efficiency; *TC* – technical progress; *MEC* –level of agricultural mechanisation; *ECO* –economic development; *DIS* – disaster rate; *FIN* – financial support; *ELE* – infrastructure; *EDU* – education

Source: Own calculations based on the National Statistical Yearbook, China Labour Statistical Yearbook, China Rural Statistical Yearbook, China Population and Employment Statistical Yearbook, China Agricultural Machinery Industry Yearbook, and Provincial Statistical Yearbooks (China Machinery Industry Information Research Institute et al. 2002–2021; National Bureau of Statistic 2002–2021a, b, c, d, e)

Model setting. This study tested the agricultural mechanisation level's effects on *TFP* by establishing a panel regression model as follows:

$$TFP_{it} = \alpha_0 + \alpha_1 \ln MEC_{it} + \alpha_2 \ln ECO_{it} + \alpha_3 \ln FIN_{it} + \alpha_4 \ln ELE_{it} + \alpha_5 \ln DIS_{it} + \alpha_6 \ln EDU_{it} + \mu_{it} + \gamma_{it} + \varepsilon_{it} \tag{2}$$

where: TFP_{it} – agricultural total factor productivity, calculated by Equation (1); μ_{it} – time fixed effect; γ_{it} –area fixed effect; ε_{it} – residual term; MEC_{it} – agricultural mechanisation level; ECO_{it} – economic development level; FIN_{it} – level of financial support; ELE_{it} – infrastructure level; DIS_{it} – disaster rate; EDU_{it} – education level.

A Hausman's test of Equation (2) revealed significance at the 1% level, and a fixed-effects model was used.

As the growth of agricultural *TFP* is cumulative, and agricultural *TFP* in the previous period affects agricultural *TFP* in the current period, the first-order lagged terms of the explanatory variables TFP_{it}, level of economic development $\ln ECO_{it}$, and financial support $\ln FIN_{it}$ are introduced in Equation (3):

$$TFP_{it} = \beta_0 + \beta_1 TFP_{it-1} + \beta_2 \ln MEC_{it} + \beta_3 \ln ECO_{it} + \beta_4 \ln ECO_{it-1} + \beta_5 \ln FIN_{it} + \beta_6 \ln FIN_{it-1} + \beta_7 \ln ELE_{it} + \beta_8 \ln DIS_{it} + \beta_9 \ln EDU_{it} + \mu_{it} + \gamma_{it} + \varepsilon_{it} \tag{3}$$

where: β – influence coefficient

Considering the interaction between variables, Equation (4) introduces the interaction terms for the infrastructure and mechanisation levels, as well as for financial support intensity and the mechanisation level:

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$$TFP_{it} = \rho_0 + \rho_1 \ln MEC_{it} + \rho_2 \ln ECO_{it} + \\ + \rho_3 \ln FIN_{it} + \rho_4 \ln ELE_{it} + \rho_5 \ln DIS_{it} + \\ + \rho_6 \ln EDU_{it} + \rho_7 \ln MEC_{it} \ln ELE_{it} + \\ + \rho_8 \ln MEC_{it} \ln FIN_{it} + \mu_{it} + \gamma_{it} + \varepsilon_{it} \tag{4}$$

where: ρ – influence coefficient.

Considering that macroeconomic variables are non-stationary, this paper conducted a unit root test to discover that *TFP* and the integrated level of agricultural mechanisation operations reject the original hypothesis at the 1% level. Thus, the study's selected variables were stationary.

RESULTS AND DISCUSSION

Mechanisation level's effect on total factor productivity. This study tested the effect of the agricultural mechanisation level on *TFP* through a fixed-effects model and subsequent regression analysis. Table 2 presents the regression results. In this table, Model (1) presents the regression results with agricultural *TFP* as the dependent variable and the agricultural mechanisation level as the independent variable, controlling for the levels of economic development, financial support, infrastructure, and education, as well as the disaster rate. As a lag exists between the level of economic development and financial support on *TFP*, and to overcome any endogeneity, the lag terms TFP_{it-1}, $\ln ECO_{it-1}$, $\ln FIN_{it-1}$ are introduced in Model (2). Considering the effect of the synergy between variables on *TFP*, Model (3) introduces interaction terms for the levels of infrastructure construction and agricultural mechanisation, and the intensity of financial support and the agricultural mechanisation level to verify any synergistic effect.

As Table 2 indicates, Models (1–3) verify that the level of agricultural mechanisation significantly contributed to *TFP*; simultaneously, *TFP* also had a cumulative effect as the previous period's *TFP* significantly affected that in the current period (0.2135). An increased economic development level promoted *TFP* (0.1375), and the previous period's economic development level, although statistically significant, affected *TFP* with an impact coefficient of approximately zero. The current and previous periods' financial support both had negative and statistically significant impacts on *TFP*, with impact coefficients of –0.0732 and –0.0658, respectively.

This is not as expected, and the possible reasons are as follows:

Table 2. Regression results for the agricultural mechanization level's effect on *TFP* (540 observations)

Variable	Model (1)	Model (2)	Model (3)
L.*TFP*	–	0.2135*** (0.0623)	–
ln*MEC*	0.0286* (0.0148)	0.0220 (0.0161)	0.1040*** (0.0236)
ln*ECO*	0.1375*** (0.0229)	–0.0102 (0.1258)	0.1571*** (0.0263)
L.ln*ECO*	–	0.1633 (0.1106)	–
ln*FIN*	–0.0732*** (0.0137)	–0.0147 (0.0227)	–0.0866*** (0.0301)
L.ln*FIN*	–	–0.0658*** (0.0226)	–
ln*ELE*	0.0161 (0.0121)	0.0166 (0.0124)	0.0894*** (0.0266)
ln*DIS*	–0.0313*** (0.0119)	–0.0330*** (0.0122)	–0.0320*** (0.0118)
ln*EDU*	–0.0029 (0.1115)	0.0491 (0.1179)	–0.0333 (0.1134)
ln*MEC* × ln*ELE*	–	–	–0.0257*** (0.0080)
ln*MEC* × ln*FIN*	–	–	0.0036 (0.0084)
Constant term	0.1832 (0.2245)	–0.2070 (0.2587)	–0.1017 (0.2399)
Individual effects	yes	yes	yes
Time effect	yes	yes	yes
R^2	0.1504	0.1275	0.0807

*$P < 0.1$, ***$P < 0.01$; L – first-order lagged term; *TFP* – total factor productivity; *EC* – technical efficiency; *TC* – technical progress; *MEC* –level of agricultural mechanisation; *ECO* – economic development; *DIS* – disaster rate; *FIN* – financial support; *ELE* – infrastructure; *EDU* – education

Source: Own calculations based on the National Statistical Yearbook, China Labour Statistical Yearbook, China Rural Statistical Yearbook, China Population and Employment Statistical Yearbook, China Agricultural Machinery Industry Yearbook, and Provincial Statistical Yearbooks (China Machinery Industry Information Research Institute et al. 2002–2021; National Bureau of Statistic 2002–2021a, b, c, d, e)

i) Binswanger (1986) found that mechanisation subsidies have small impacts on output and can even harm employment. According to the theory of diminishing marginal returns, as the level of financial support increases, the marginal returns trend toward zero, and

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the promotion effect on *TFP* decreases or even has a negative impact.

ii) The type of financial subsidy is irrational and does not apply to productivity improvement; resources are mismatched, with financial subsidies favouring larger farms and wealthier regions (Binswanger 1986), which is not conducive to improving smallholder farmers' *TFP*. According to the Third National Agricultural Census, 207.43 million agricultural operating households were operating nationwide in 2016, including 3.98 million large-scale agricultural operating households, indicating that 98% of China's agricultural operating households were smallholders, specifically small-scale operators.

iii) Due to the existence of externalities, local governments are reluctant or even discouraged to invest in soft public goods, such as science and technology, with long-term effects under fiscal decentralisation. This is especially the case under the 'GDP championship system', as science and technology investments in agriculture are more likely to be neglected, and local governments have shirked their responsibility to support and promote agricultural R&D in various ways. Some have even 'stopped milking and cutting off food' to grassroots agricultural extension institutions; this seriously affects the technological progress and technical efficiency on the agricultural frontier, negatively affecting the growth of agricultural *TFP*.

iv) A time lag exists between financial subsidies. In particular, the current year's fiscal subsidies are not yet paid out during the spring cultivation period, resulting in farmers deciding their farming behaviour in the current period based on the previous year's level of fiscal support. This leads to the level of financial support negatively affecting *TFP*. The disaster rate and education level negatively affected *TFP*, but the latter's effect was not statistically significant. Introducing the interaction term reveals that rural infrastructure development can contribute to *TFP* but the interaction term between the level of rural infrastructure and that of agricultural mechanisation negatively affected *TFP* (–0.0257), suggesting a negative synergistic effect between rural infrastructure development and the level of agricultural mechanisation. It is likely that the level of financial support was not conducive to *TFP* (–0.0866) due to the use of rural electricity for other purposes, while the coefficient of the interaction term between the levels of financial support and agricultural mechanisation had a positive but statistically insignificant effect on *TFP*.

Influence path of agricultural mechanisation level on total factor productivity. To verify the mechanisation level's path of influence on *TFP*, this study decomposed the *TFP* index into technical efficiency and technical progress indexes and conducted regressions. Models (4) and (7) calculate the regression results for the fixed-effect model of agricultural mechanisation and the technical efficiency and technical progress levels, respectively; Models (5) and (8) denote the regression results of the technical efficiency and technical progress levels, economic development level, and financial support intensity by one period, respectively; and Models (6) and (9) indicate the regression results from introducing the interaction terms for the infrastructure construction and agricultural mechanisation levels, and the financial support and agricultural mechanisation level, respectively.

As Table 3 demonstrates, the agricultural mechanisation level improved technical efficiency and promoted technological progress, but it was not statistically significant. The economic development level significantly and positively contributed to technical efficiency and technical progress, while the intensity of financial support negatively affected them, further validating the previous section's findings. The introduction of the lagged term revealed that the level of economic development in the previous period promoted technical progress but negatively affected technical efficiency. The coefficients for financial support's effect on technical efficiency and technical progress in the previous period were 0.0952 and –0.1438, respectively. This is likely because of the lagged nature of financial support and the irrational financial support programme, which can certainly promote technical efficiency but inhibits technical progress. Specifically, the coefficient of educational level's effect on technical efficiency is negative but can promote agricultural technical progress. This is possibly because the rural labour force flows to urban areas or engages in other non-agricultural activities as rural residents' educational level increases. Moreover, the remaining agricultural labour force decreases and tends to skew older and more often female as a result, which is not conducive to improving technical efficiency. However, the number of 'new' farmers is simultaneously and gradually expanding. This group is more educated and can master advanced modern production skills that can drive technological progress in agriculture. The coefficient of the interaction between the agricultural mechanisation level and financial support was negative, indicating a synergistic effect between the two. The rural infrastructure level can promote technical progress, but the interaction term between the levels of rural infrastructure

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Table 3. Study of the agricultural mechanization level's path of impact on *TFP* (540 observations)

Variable	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)
L.*EC*	–	–0.0308 (0.0460)	–	–	–	–
L.*TC*	–	–	–	–	–0.1277** (0.0553)	–
ln*MEC*	0.0215 (0.0222)	0.0173 (0.0236)	0.0469 (0.0358)	0.0124 (0.0207)	0.0267 (0.0212)	0.0543 (0.0333)
ln*ECO*	0.0760** (0.0344)	0.7506*** (0.1876)	0.1201*** (0.0398)	0.0829*** (0.0321)	–0.9352*** (0.1700)	0.0548 (0.0370)
L1.lne*ECO*	–	–0.6311*** (0.1640)	–	–	0.9692*** (0.1484)	–
ln*FIN*	–0.0394* (0.0205)	–0.1631*** (0.0337)	0.0456 (0.0457)	–0.0432** (0.0191)	0.1278*** (0.0302)	–0.1438*** (0.0425)
L1.ln*FIN*	–	0.0952*** (0.0338)	–	–	–0.1432*** (0.0306)	–
ln*ELE*	0.0187 (0.0181)	0.0191 (0.0184)	–0.0213 (0.0404)	–0.0041 (0.0169)	–0.0041 (0.0165)	0.1039*** (0.0375)
ln*DIS*	0.0108 (0.0179)	0.0232 (0.0183)	0.099 (0.0178)	–0.0372** (0.0167)	–0.0559*** (0.0163)	–0.0369** (0.0166)
ln*EDU*	–0.3840** (0.1672)	–0.4800*** (0.1758)	–0.4773*** (0.1721)	0.2320 (0.1560)	0.3768** (0.1574)	0.3016* (0.1597)
ln*MEC* × ln*ELE*	–	–	0.0125 (0.0122)	–	–	–0.0363*** (0.0113)
ln*MEC* × ln*FIN*	–	–	–0.0268** (0.0128)	–	–	0.0311*** (0.0119)
Constant term	1.1141*** (0.3366)	1.0284*** (0.3763)	0.8627** (0.3641)	0.2048 (0.3142)	0.4222 (0.3502)	0.2085 (0.3380)
Individual effects	yes	yes	yes	yes	yes	yes
Time effects	yes	yes	yes	yes	yes	yes
R^2	0.1061	0.318	0.0093	0.0429	0.1475	0.0318

*,**,*** $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively; L – first-order lagged term; *TFP* – total factor productivity; *EC* – technical efficiency; *TC* – technical progress; *MEC* –level of agricultural mechanisation; *ECO* –economic development; *DIS* – disaster rate; *FIN* – financial support; *ELE* – infrastructure; *EDU* – education

Source: Own calculations based on the National Statistical Yearbook, China Labour Statistical Yearbook, China Rural Statistical Yearbook, China Population and Employment Statistical Yearbook, China Agricultural Machinery Industry Yearbook, and Provincial Statistical Yearbooks (China Machinery Industry Information Research Institute et al. 2002–2021; National Bureau of Statistic 2002–2021a, b, c, d, e)

and agricultural mechanisation was unfavourable for technical progress (–0.036).

Sub-regional test. This study further analysed whether regional heterogeneity exists in the agricultural mechanisation level's effects on agricultural *TFP* by dividing the 540 samples from 27 provinces spanning 2001–2020 into three equal groups as per *TFP* levels (Table 4).

Table 5 shows the regional heterogeneity analysis results regarding the agricultural mechanisation level's effect on *TFP* after introducing the lag term; in this table, Models (10–12) demonstrate the effects of agricultural mechanisation level on agricultural *TFP* in the

Table 4. Regions grouped by total factor productivity

Group	Regions
Highest	Zhejiang, Heilongjiang, Shandong, Jiangsu, Hebei, Gansu, Henan, Fujian, Jiangxi
Middle	Jilin, Ningxia, Anhui, Liaoning, Xinjiang, Inner Mongolia, Shaanxi, Hubei, Guangdong
Lowest	Shanxi, Yunnan, Hunan, Chongqing, Guizhou, Guangxi, Sichuan, Hainan, Qinghai

Source: Own processing based on the National Statistical Yearbook, China Labour Statistical Yearbook, and China Rural Statistical Yearbook (National Bureau of Statistic 2002–2021a, c, d)

https://doi.org/10.17221/291/2023-AGRICECON

Table 5. Regional heterogeneity analysis of the agricultural mechanization level's impact on TFP after introducing the lagging term (180 observations)

Variable	Highest			Middle			Lowest		
	Model (10)	Model (11)	Model (12)	Model (13)	Model (14)	Model (15)	Model (16)	Model (17)	Model (18)
L.*TFP*	0.1245 (0.1560)	–	–	0.1674 (0.1415)	–	–	0.1956** (0.0887)	–	–
L.*EC*	–	–0.0092 (0.0853)	–	–	–0.0008 (0.0862)	–	–	–0.1250 (0.0781)	–
L.*TC*	–	–	–0.0796 (0.1166)	–	–	–0.0752 (0.1201)	–	–	–0.2268*** (0.0809)
ln*MEC*	0.0112 (0.0316)	0.0050 (0.0324)	0.0140 (0.0372)	0.0076 (0.0345)	0.0002 (0.0518)	–0.0184 (0.0555)	0.0146 (0.0324)	0.0930* (0.0547)	0.0074 (0.0410)
ln*ECO*	0.0465 (0.2326)	0.9982*** (0.2449)	–1.0066*** (0.2820)	0.1238 (0.1611)	0.6270*** (0.2400)	–0.6571** (0.2607)	–0.2200 (0.2643)	0.7541* (0.4482)	–1.2503*** (0.3424)
L1.ln*ECO*	0.1795 (0.2053)	–0.8238*** (0.2147)	1.0538*** (0.2473)	0.0238 (0.1419)	–0.6045*** (0.2100)	0.7683*** (0.2275)	0.3602 (0.2303)	–0.4968 (0.3874)	1.1600*** (0.2956)
ln*FIN*	–0.0297 (0.0432)	–0.0930** (0.0446)	0.0578 (0.0519)	–0.0329* (0.0300)	–0.1400*** (0.0455)	0.0961** (0.0485)	0.0463 (0.0454)	–0.2418*** (0.0775)	0.2433*** (0.0578)
L1.ln*FIN*	–0.0817* (0.0428)	–0.0027 (0.0459)	–0.0753 (0.0535)	–0.0577 (0.0301)	0.1202** (0.0465)	–0.1502*** (0.0500)	–0.0900** (0.0444)	0.0978 (0.0749)	–0.1759*** (0.0571)
ln*ELE*	–0.0285 (0.0466)	0.0180 (0.0483)	–0.0432 (0.0555)	0.0272 (0.0296)	0.0325 (0.0295)	–0.0063 (0.0316)	0.0165 (0.0183)	0.0072 (0.0309)	0.0016 (0.0233)
ln*DIS*	–0.0900*** (0.0213)	0.0128 (0.0220)	–0.1061*** (0.0253)	–0.0175 (0.0166)	–0.0126 (0.0250)	–0.0074 (0.0267)	0.0079 (0.0254)	0.0703 (0.0430)	–0.0571* (0.0325)
ln*EDU*	0.2073 (0.1671)	–0.0609 (0.1730)	0.2572 (0.1988)	0.1188 (0.1973)	–0.4454 (0.2956)	0.4856 (0.3153)	–0.2212 (0.2736)	–1.1579** (0.4629)	0.5349 (0.3491)
Constant term	–0.4168 (0.4511)	–0.1309 (0.4539)	0.9830* (0.5674)	–0.2658 (0.4440)	1.6700*** (0.6088)	–0.3536 (0.6803)	0.1475 (0.5072)	1.3257 (0.8451)	0.9094 (0.6577)
Individual effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.1263	0.0076	0.1226	0.0407	0.1045	0.1574	0.1932	0.0668	0.2195

*,**,*** $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively; L – first-order lagged term; *TFP* – total factor productivity; *EC* – technical efficiency; *TC* – technical progress; *MEC* –level of agricultural mechanisation; *ECO* –economic development; *DIS* – disaster rate; *FIN* – financial support; *ELE* – infrastructure; *EDU* – education

Source: Own calculations based on the National Statistical Yearbook, China Labour Statistical Yearbook, China Rural Statistical Yearbook, China Population and Employment Statistical Yearbook, China Agricultural Machinery Industry Yearbook, and Provincial Statistical Yearbooks (China Machinery Industry Information Research Institute et al. 2002–2021; National Bureau of Statistic 2002–2021a, b, c, d, e)

highest group; Models (13–15) show the effects of agricultural mechanisation level on *TFP* in the middle group; and Models (16–18) show the effects of agricultural mechanisation.

Table 6 shows the regional heterogeneity analysis results regarding the level of agricultural mechanisation of agricultural *TFP* after introducing the interaction term. In this table, Models (19–21) reveal the effects of the highest group of agricultural mechanisation levels on *TFP*; Models (22–24) show the effects from the middle group; and Models (25–27) show the effects from the lowest group.

According to Tables 5 and 6, the agricultural mechanisation level positively affected agricultural *TFP* in the

https://doi.org/10.17221/291/2023-AGRICECON

Table 6. Regional heterogeneity analysis of the agricultural mechanization level's impact on TFP after introducing the interaction term (180 observations)

Variable	Highest			Middle			Lowest		
	Model (19)	Model (20)	Model (21)	Model (22)	Model (23)	Model (24)	Model (25)	Model (26)	Model (27)
ln*MEC*	0.0535 (0.0825)	0.0633 (0.0880)	–0.0215 (0.1021)	0.0570 (0.0950)	0.3284** (0.1492)	–0.3036* (0.1611)	0.1577*** (0.0541)	0.2640*** (0.0921)	–0.0038 (0.0760)
ln*ECO*	0.2100*** (0.0442)	0.0915** (0.0472)	0.1129** (0.0547)	0.0855** (0.0383)	0.0804 (0.0602)	0.0155 (0.0650)	0.2406*** (0.0628)	0.3793*** (0.1069)	–0.0560 (0.0881)
ln*FIN*	–0.0363 (0.0766)	0.0895 (0.0817)	–0.1384 (0.0948)	–0.1715** (0.0800)	0.1741 (0.1256)	–0.3701*** (0.1356)	–0.1267*** (0.0474)	–0.0111 (0.0806)	–0.1200* (0.0665)
ln*ELE*	–0.0472 (0.1126)	0.0037 (0.1200)	–0.0504 (0.1392)	0.1312*** (0.0504)	0.0895 (0.0792)	0.0530 (0.0856)	0.1667*** (0.0500)	0.0465 (0.0850)	0.1142 (0.0701)
ln*DIS*	–0.0871*** (0.0202)	–0.01117 (0.0215)	–0.0759*** (0.0297)	–0.0168 (0.0158)	–0.0170 (0.0248)	–0.0006 (0.0268)	0.0009 (0.0245)	0.0635 (0.0417)	–0.0503 (0.0344)
ln*EDU*	0.1254 (0.1702)	–0.1695 (0.1815)	0.2850 (0.2105)	0.1791 (0.1911)	–0.3805 (0.3001)	0.4919 (0.3240)	–0.4566* (0.2527)	–1.2127*** (0.4299)	0.4001 (0.3546)
ln*MEC* × ln*ELE*	0.0032 (0.0266)	0.0116 (0.0283)	–0.0074 (0.0329)	–0.0297** (0.0127)	–0.0084 (0.0199)	–0.0239 (0.0215)	–0.0599*** (0.0184)	–0.0240 (0.0313)	–0.0392 (0.0258)
ln*MEC* × ln*FIN*	–0.0163 (0.0205)	–0.0353 (0.0218)	0.0223 (0.0253)	0.0276 (0.0226)	–0.0611* (0.0354)	0.0952** (0.0382)	0.0154 (0.0140)	–0.0426* (0.0239)	0.0446** (0.0200)
Constant term	–0.1857 (0.4698)	0.3354 (0.5009)	0.5743 (0.5810)	0.0570 (0.5478)	–0.0562 (0.8603)	1.2791 (0.9286)	–0.1805 (0.5031)	–0.0990 (0.8559)	0.8538 (0.7059)
Individual effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.1078	0.0004	0.0159	0.0614	0.0135	0.0721	0.0135	0.0417	0.0590

*,**,*** $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively; *TFP* – total factor productivity; *EC* – technical efficiency; *TC* – technical progress; *MEC* –level of agricultural mechanisation; *ECO* –economic development; *DIS* – disaster rate; *FIN* – financial support; *ELE* – infrastructure; *EDU* – education

Source: Own calculations based on the National Statistical Yearbook, China Labour Statistical Yearbook, China Rural Statistical Yearbook, China Population and Employment Statistical Yearbook, China Agricultural Machinery Industry Yearbook, and Provincial Statistical Yearbooks (China Machinery Industry Information Research Institute et al. 2002–2021; National Bureau of Statistic 2002–2021a, b, c, d, e)

three groups, with the largest effect in the lowest group (0.0146) and increasing technical efficiency in the lowest group (0.0930). A lagged effect also occurred, with the previous period's agricultural *TFP* positively affecting agricultural *TFP* in the current period, and the largest and statistically significant effect was observed in the lowest group (0.1956).

The economic development level can increase the agricultural technical efficiency (*EC)*; by region, this had the greatest effect on the highest group (0.9982), followed by the lowest group (0.7541) and the middle group (0.6270). In terms of the impact path, the level of economic development negatively impacted *EC* in the three groups of regions, with the greatest impact on the highest group (–0.8238), followed by the middle group (–0.6045), and the lowest impact on the lowest group (–0.4968). Meanwhile, the increase in the economic development level was detrimental to technological progress, with the greatest negative impact on the lowest group (–1.2503), followed by the highest group (–1.0066), and the lowest impact on the middle group (–0.6571). Therefore, although an increase in the economic development level can promote technical efficiency, it is detrimental to technological progress.

The intensity of financial support in both the current and previous periods negatively affected all three groups of regions, with the largest negative effect on the lowest group's technical efficiency (–0.2418), indicating that China's policies to financially support agriculture are inadequate and can widen the gap in agricultural productivity across regions. Introducing the interaction term revealed that the interaction term

https://doi.org/10.17221/291/2023-AGRICECON

between the levels of agricultural mechanisation and infrastructure negatively affected the nine provinces in the lowest group (–0.0599). Further, the interaction term between the level of agricultural mechanisation and the strength of financial support negatively affected the highest group and had a positive but statistically insignificant effect on the middle and lowest groups.

CONCLUSION

Agricultural mechanisation provides important support for agricultural modernisation and is the foundation for a strong agricultural country. In this study, 540 observations from 27 provinces in China spanning 2001–2020 were selected to verify the characteristics and impact paths of the agricultural mechanisation level on agricultural *TFP* from different perspectives. The research complements the contributions of agricultural mechanisation. It also empirically tested the impact path and regional heterogeneity of the agricultural mechanisation level on *TFP* in China and provided policy recommendations for building the nation as an agricultural power. The findings were as follows:

i) The agricultural mechanisation level can promote agricultural *TFP*, and simultaneously, a cumulative effect exists. Agricultural *TFP* in the previous period can also significantly affect agricultural *TFP* in the current period.

ii) By analysing agricultural mechanisation's path of impact on agricultural *TFP*, we observed that the agricultural mechanisation level improved technical efficiency and promoted technological progress, but this was not statistically significant.

iii) We examined regional heterogeneity in the agricultural mechanisation's impact on agricultural *TFP* to note that the agricultural mechanisation level positively impacted agricultural *TFP* in the three groups of regions. The largest impact (0.0146) and largest increase in technical efficiency (0.0930) occurred in the lowest group, which was mostly located in the central and western parts of China.

iv) The levels of economic development and financial support were the main factors influencing agricultural *TFP*. The economic development level can improve agricultural *TFP* (0.1375), and both current and previous financial support had negative and statistically significant effects on agricultural *TFP*, with coefficients of –0.0732 and –0.0658, respectively. Economic development significantly and positively affected technical efficiency and technological progress, while financial support affected them negatively. By region, the economic development level had the largest effect on agricultural *EC* in the highest group (0.9982), followed by the lowest group (0.7541) and the middle group (0.6270). The intensity of financial support negatively affected all three groups of regions, with the largest negative effect on the lowest group's technical efficiency (–0.2418).

Combining the reality of China and this study's findings reveals that agricultural mechanisation in China can be further encouraged and developed by the following three policy measures: first, agricultural machinery should be increasingly promoted. Effective progress in agricultural science and related technologies depends on not only innovations in science and technology itself but also the strong support of a system to promote agricultural science and technology in particular. Therefore, the system to promote agricultural machinery should be improved, while further motivating the staff within this system. Second, policies must further address the heterogeneity between regions, and the development of agricultural mechanisation should focus on the central and western regions. Although the agricultural mechanisation level has a greater impact on the factor-level agricultural productivity, the agricultural *TFP* is low, and a gap exists in the eastern region, but with significant development potential. Finally, subsidy policies for agricultural machinery should be further adjusted. The government should guide the development of local agricultural mechanisation in policies and increase agricultural machinery research investments to promote efficient agricultural technology, technical progress in agriculture, and the growth of agricultural *TFP*. Simultaneously, any subsidy policy should be adjusted according to the actual situation in each region to reduce the differences in agricultural productivity.

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Received: September 2, 2023
Accepted: November 1, 2023