The Impact of Big Data Technology on The Speed and Contribution of Scientific and Technological Progress in Food Production

——Based on the Establishment of Big Data Bureau and Provincial Panel Data From

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Abstract. The use of agricultural big data technology is crucial for the production of food. Based on the establishment of China's Big Data Bureau and the provincial panel data from 1949 to 2020, this paper found that the establishment of China's big data Bureau promoted the promotion and application of big data technology, and significantly increased the rate of scientific and technological progress and the role of the contribution rate in grain production. With 1949 as the base period, the contribution rate of scientific and technological progress in grain production increased by 2.9% from 1985 to 2010, and was 0.6% even after controlling for provinces and years, with the result being significant at 1% level. The study of this paper provides positive evidence for the impact of big data technology on grain production, and provides suggestions for the stability and security of grain production in China.

Keywords: Food Production; Scientific and Technological Progress;Contribution;Big Data; Big Data Bureau

1 Introduction

Agriculture is the backbone of the country's economy and is essential for social, political, and economic stability. The continuous growth of China's agriculture has proved its ability to achieve basic self-sufficiency in agricultural products, especially grain (Huang Jikun, 1996). However, as an important commodity for the national economy and people's livelihood, food is the foundation of foundation. Its production is closely related to resource endowment, climate change and factor supply, meanwhile risks and uncertainties are also increasingly intensified, resulting in greater volatility of food output. Maintaining the stability and security of food production has

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always been an important goal of the Chinese government's agricultural policy (Zhong Funing, 2006).

Under the current restrictive conditions, only scientific and technological progress is the primary productive force that can strengthen grain production capacity, activate grain production vitality, increase farmers' incomes and ensure food security. In the era of big data, what is the speed of scientific and technological progress in China's regional grain production? Will big data technology assist boost both the contribution of scientific and technological advancement to grain production and grain production itself? The discussion of these problems makes the pertinence, timeliness and completeness of food production related policy making in China, and provides a solid foundation for resolving the bottleneck of resource and environment constraints, realizing the balance of food supply and ensuring food security. This study provides evidence for the effect of big data technology on grain production and provides suggestions for the stability and security of grain production.

Most of scholars believe that scientific and technological breakthrough is an important driving force for food production, but there is comparatively little research on the rate and impact of scientific and technological advancement in food production, and the majority of studies solely focus on qualitative and descriptive statistics.Occasionally, empirical research is only limited to a single food crop, lacking the understanding of the overall law. In addition, most research methods are based on time series data with small sample size, and the reliability needs to be further improved. In addition, big data technology is a relatively special existence in the Internet technology system. Current literatures (such as Xu Weixia and Zhang Hongxi, 2022) found in the process of studying big data technology that its application in agricultural production had important practical significance, but there was no empirical analysis and no specific influence mechanism was proposed. Based on the improved multi-factor second-level CES production function and the provincial panel data of China from 1949 to 2010, this paper constructs an appropriate empirical model of panel data to analyze the rate and impact of scientific and technological development in grain production. This research examines the promotion impact of the Big Data Bureau's formation in Chinese provinces on big data technology. This study also examines whether big data technologies may boost grain output and the rate at which scientific and technical advancements contribute to grain production growth. On the basis of the findings, pertinent policy suggestions are put forth.

The arrangement of this paper is as follows: the second part is literature review, including the theoretical and empirical research related to food production, the relevant application of big data and the impact of capital deepening on agricultural economy and other perspectives; the third part is about model description and methods; the fourth part is the result of data analysis; and the conclusion in the last part.

2 Literature Review

2.1 Theoretical and Empirical Research on Food Production

Borjas (2004) found that a 10 percent cut in public assistance would increase the percentage of food-insecure households to about 5 percent. Tilman (2002) argued that technological progress and current economic forces, including agricultural subsidies in the United States, the European Union and Japan, had played an important role in increasing food supply and reducing the cost of agricultural products. Neumann and Verburg (2010) analyzed the production efficiency and influencing factors of wheat, corn, rice and other food crops, and believed that irrigation, transportation, market influence, agricultural labor force and slope were significantly positively correlated with food production efficiency.

In China, Wu Shanlin (2000) calculated and statistically analyzed the dynamic proportion of grain production in China's total grain production by provinces and regions, and showed that China's grain production had stable regional variation characteristics since the market-oriented reform. Lu Feng and Xie Ya (2008), Huang Jikun et al. (2009) studied the periodicity, change trend and causes of grain price fluctuations in China, and put forward policy suggestions on stabilizing grain prices. Xu Qing and Yin Rongliang (2011) investigated the existence of scale economies in the production of major food crops in China from the perspectives of input-output and production cost based on the field survey data of 1049 farmers in 100 villages in five major grain-producing provinces in China. Liu Chengyu (2011) believed that the quantity and quality of cultivated land were the two foundations of China's grain production and food security system. Huang Jikun et al. (2011) analyzed in detail the effects of direct grain subsidies and comprehensive agricultural subsidies, and found that subsidies did not distort the market and had no impact on food production and agricultural input.

According to the literature, the influencing factors of the speed and contribution rate of technological progress include fixed input, agricultural expenditure policy variable (EP), agricultural tax variable (TP), big data technology and so on. As stated by Huang Weihong (2006), rural fixed asset investment is an important material basis for agricultural economic growth, rural social progress and farmers' income increase, which was of great significance to grain production. Chen et al. (2010) analyzed the impact of tax variables and agricultural expenditure policies on grain output.

2.2 Big Data Related Applications

Big data is a data set characterized by large volume, many types, fast reading and writing speed and high utilization value. Big data technology is a product, system and solution that can meet the application requirements of big data and has the dual attributes of product and service. Begenau et al. (2018) defined big data as a by-product of economic activities, and believed that big data might benefit large companies with active business activities and massive data generation. The current literature mainly analyzed the relationship between big data technology and enterprise value and production efficiency.

Li tang (2020) showed that data management ability can improve productivity. Specifically, the proper application of big data can improve macro and micro forecasting, enhance production efficiency and enterprise value (Brynjolfsson et al., 2011; Chen et al., 2018). Brynjolfsson and Mitchell (2017) believed that big data technology may replace human resources in some production and operation links, thus saving enterprises' labor costs. Mikalef et al. (2018) believed that the targeted use of big data analysis could enhance the organizational management ability of enterprises, realize the optimization of organizational management, and promote enterprises to obtain competitive advantages. Secondly, the application of big data technology could enhance the value of enterprises by promoting R&D innovation. Big data technology can provide research and demonstration support for enterprise R&D innovation by better analyzing the characteristics of industry demand and innovation elements. In the process of R&D innovation, big data technology might improve the efficiency of R&D activities, for example, artificial intelligence was a new general "R&D method" that could reconstruct the essence of R&D innovation process (Cockburn et al., 2019).

Agricultural big data technology took agricultural production work as the main object, took the Internet and computer as the basis, realized the in-depth mining of agricultural production work information through the application of corresponding data processing technology, and then understood the current situation of agricultural production according to the data information, and the relevant data could provide sufficient support for agricultural production decision-making. Since the birth of agricultural big data technology, the state had attached great importance to the application and development of this technology, and provided corresponding policy support for the establishment of agricultural big data technology standards (Lu, 2021). Relevant agricultural technology departments had also actively explored the application of agricultural big data technology and achieved certain results, which had further improved the efficiency and scientificity of agricultural production.

For the upstream and downstream enterprises of agricultural production, no matter production enterprises, processing enterprises or sales enterprises, they could mine more market dynamics through agricultural big data, and obtained agricultural production and operation information dynamically and continuously through the Internet and computers (Meng, 2021). It can be seen that the effective application of agricultural big data technology in agricultural economic management would improve the economic structure of agricultural production and provided sufficient guarantee for the efficient and sustainable development of agricultural production (Xu and Zhang, 2022).

2.3 Other Perspectives

Other literature explored the impact of capital deepening on the agricultural economy. For example, Luo (2013) calculated the ratio of agricultural stock capital-output in China from 1980 to 2011, and conducted regression analysis on the ratio of stock capital-output and the agricultural economic growth rate, and found that there was a significantly negative correlation between these two variables. Pan et al. (2007) believed that in order to ensure the sustainable and stable development of agriculture and sound structural adjustment, sufficient capital investment must be given to agriculture. Gao (2010) believed that capital deepening was one of the basic ways to improve agricultural labor efficiency, and "the degree of capital deepening scales the degree of agricultural modernization in a certain sense." When studying the relationship between China's economic growth and capital formation, Zhang Jun (2002) found that for the economy with unlimited population supply, as long as capital formation could attract and match more labor, it would take a long time for the economy to reach the "steady state" of growth, and the rise of capital density was usually after full employment.

3 Model and Research Method

Table 1. Variable Definition

Variable	Symbol	Definition
Explained Variable	ROT_{it}	Represents the contribution rate of technological progress to grain output in t year of province i
Explanatory Variable	dc	For the establishment of a big data bureau, dc is 1 if the big data bureau was established in the previous year , and 0 otherwise
Intermediate calculation variable	γ_{it}	Represents the technological progress rate of province i in year t
	GR_{it}	Grain output level of the i province in year t
	ER_{it}	Input of land factor for grain production in province i in year t
	CP_{it}	Capital factor input of grain production in province i in year t
	LNGR	Logarithm of GR_{it}
	LNER	Logarithm of ER_{it}
	LNLR	Logarithm of LR_{it}
	LNCP	Logarithm of CP_{it}
	LNCP_ER	CP_{it} dived ER_{it}，take logarithm
	LNCP_ER2	LNCP_ER squared

LNCP_LR	CP_{it} divide LR_{it}，take logarithm

3.1 Model

Based on the CES production function model proposed by Arrow, Chenery, Mihas and Solow et al. (1961) and the multi-factor second-level CES production function model of Sato(1967), this paper builds an improved multi-factor second-level CES production function model to carry out an analysis of the speed of scientific and technological progress in grain production, with reference to Jiang Song et al. (2012). . Variables definition are shown in Table 1. Based on this, an improved multi-factor second-level CES production function framework between input and output factors in grain production is introduced:

$$GR_{it1} = (\alpha_1 CP_{it}^{-\theta_1} + \alpha_2 ER_{it}^{-\theta_1})^{1/\theta_1} \quad (1)$$

$$GR_{it1} = Ae^{\gamma t}(\beta_1 GR_{it1}^{-\theta} + \beta_1 LR_{it}^{-\theta})^{-m/\theta} \quad (2)$$

In Equation (1), i= 1, 2... , 31, represents the province code. t is time, and t = 1985,1986,... , 2020. GR_{it1} denotes the grain output of province i in year t, that is, the first-level production function. CP_{it} represents the capital factor input of grain production in the i'th province in year t; ER_{it} represents the land factor input of grain production in the i'th province in year t; α_1、α_2 represents the influence coefficients of capital factor input and land factor input on grain output, namely, the parameters to be estimated, and θ_1 is the distribution coefficient. In Equation (2), LR_{it} is the labor input in grain production, A is the comprehensive benefit index, which reflects the broad technical level, including not only the improvement of factor quality, but also the improvement of management level and other factors that have an important impact on grain output. γ is the annual technological progress rate; A represents the time-related multiple * of output increase caused by the improvement of technology level; β_1 and β_2 represents the parameters to be estimated of the second-level CES production function; and θ is the distribution coefficient. When m is greater than 1, the returns to scale of grain production are increasing; when m is less than 1, the returns to scale of grain production are decreasing; and when m is 1, the returns to scale are constant.

Equations (1) and (2) show that the second-level CES production functions are nonlinear functions, which need to be log-linearized. First, taking the logarithm of both sides of Equation (2), we can obtain:

$$LNGR_{it1} = LNA + \gamma t + \beta_1 mLNGR_{it1} + \beta_2 mLNGR_{it1} - {}^{1}/_{2}\,\theta m \beta_1 \beta_2 (LN\, {}^{GR_{it1}}/_{LR_{it1}})^2 \quad (3)$$

Furthermore, the Taylor series of Equation (3) is expanded at θ=0, and the order 0, 1 and 2 approximations are taken. At the same time, considering the factors that may cause Multicollinearity and computational complexity, the model is screened and deleted by stepwise regression (Li and Pan, 2005), and the random error term-μ_{it}, is added to obtain the final regression analysis model of this paper:

$$\mathrm{LNGR_{it}} = \mathrm{LNA} + \gamma t + \beta_1 m\alpha_1 \mathrm{LNCP_{it}} + \beta_1 m\alpha_2 \mathrm{LNER_{it}} + \beta_2 \mathrm{LNLR_{it}} - {}^1\!/_2\, m\beta_1\theta_1\alpha_1\alpha_2(\mathrm{LN}\, {}^{\mathrm{CP_{it}}}\!/_{\mathrm{ER_{it}}})^2 - {}^1\!/_2\, \theta m\beta_1\beta_2(\mathrm{LN}\, {}^{\mathrm{CP_{it}}}\!/_{\mathrm{LR_{it}}})^2 + \mu\, \mathrm{it} \tag{4}$$

The basic formula for solving the contribution rate of scientific and technological progress to grain yield increase is as follows:

$$ROT_{it} = {}^{\gamma_{it}}\!/_{PGR_{it}} \times 100\% = {}^{\gamma_{it}}\Big/_{\sqrt[n]{{}^{GR_{it_n}}\!/_{GR_{it_0}}} - 1} \times 100\% \tag{5}$$

In Equation (5), $\mathrm{ROT_{it}}$ represents the contribution rate of technological progress in province i in year t to grain output, $\mathrm{PGR_{it}}$ represents the speed of technological progress in province i in year t, $\mathrm{GR_{itn}}$ represents the average growth rate in province i in year t, $\mathrm{GR_{it0}}$ represents the grain output in the reporting period of province i in year t, and represents the grain output in the base period of province i in year t. There are two ways to choose the base period. In the first way, the base period is the year with the earliest record of grain production in each province. The second way, according to the fixed year 2000,2010. In this paper, the first method is used as the main analysis, and the second method is used as the robustness test.

After obtaining the above indicators, the following regression analysis is done

$$ROT_{it} = \alpha + \beta_{d1} dc_{it} + \beta_{d2} X_{it} + \varepsilon_{it} \tag{6}$$

Among them, $\mathrm{dc_{it}}$ is the variable of whether the big data bureau of province i in year t is established, $\mathrm{X_{it}}$ is the control variable, and ε_{it} is the interference term.

3.2 Data Explanation

In order to make the research conclusions more reliable, based on the improved multi-factor second-level CES production function, this paper uses the provincial panel data from 1949 to 2010 to analyze the speed and contribution of scientific and technological progress in China's grain production. The total grain output, $\mathrm{GR_{it}}$, is used to represent the level of grain output, the sown area of grain crops, $\mathrm{ER_{it}}$, is used to represent the input of land factor in grain production, and the total power of agricultural machinery, $\mathrm{CP_{it}}$, is used to represent the input of capital factor in grain production. Due to the lack of statistical data on the total power of agricultural machinery in all provinces in 2006, the average value of 2005 and 2007 is adopted in the actual calculation, and the number of agricultural labor force, $\mathrm{LR_{it}}$, is used to represent the labor input in grain production. All the above data come from China

Statistical Yearbook (calendar years), China Rural Statistical Yearbook (calendar years), Statistical Data Compilation of the Sixty Years of the People's Republic of China, statistical bulletins of relevant years in various provinces, as well as CSMAR database of CSMAR Data Service Center and Zhonghong Teaching and Research Support System (MCDB). Table 2 shows the descriptive statistics of each variable.

3.3 Research Idea

Based on the above analysis, I put forward the hypothesis that the establishment of the big data bureau in each province has a promotion effect on the big data technology, and it is expected that after the establishment of the big data bureau, the speed and contribution of scientific and technological progress in grain production in the corresponding province will increase. It is verified by provincial panel data. Through regression analysis (6), we can obtain the impact of the establishment of the big Data bureau on the contribution rate of technological progress to grain output, β_{d1}. If β_{d1} is positive and significant, the hypothesis is valid.

4 Empirical Result

In order to analyze the impact of agricultural big data on the improvement of agricultural production, this paper uses the statistical data of the establishment of the Big Data Bureau from 1949 to 2020 to carry out the overall regression. Since the big Data Bureau was not established before 2015, this paper only shows the data and variables from 2016 to 2020.

Table 2. Descriptive Static of Founding Variable of the Big Data Bureau

Years	Number	Mean	Standard Deviation	Min	Max
1949-2020	1616	0.02	0.14	0	1
2016	29	0.03	0.19	0	1
2017	29	0.03	0.19	0	1
2018	29	0.03	0.19	0	1
2019	29	0.38	0.49	0	1
2020	30	0.53	0.51	0	1

Note: Before 2015, there was no big data bureau, so this table only shows the statistical results of all variables and the statistical results after 2015.

As shown in Table 2, there are 1616 data collected in this paper from 1949 to 2020. The mean value of the establishment variable of the big data bureau in the province is 0.02, the standard deviation is 0.14, the minimum value is 0, and the maximum value is 1. From 2016 to 2020, different provincial administrative units gradually set up big data bureaus, and the mean value of corresponding variables increased from 0.03 in 2016 to 0.53 in 2020.

Table 3. Descriptive Static of variables related to grain production

Variable	Number	Mean	Standard Deviation	Mean	Max
LNGR	1616	6.75	1.14	3.15	8.93
LNER	1616	7.84	1.09	3.84	9.58
LNLR	1616	6.51	1.04	3.3	8.18
LNCP	1616	6.11	2.11	-4.61	9.5
LNCP_ER	1616	-1.73	2.08	-13.15	1.24
LNCP_ER2	1616	7.34	17.82	0	172.86
LNCP_LR	1616	-0.13	1.7	-9.55	2.53

As shown in Table 3, from 1949 to 2020, the mean value of the log LNGR of grain output level in each province is 6.75, the standard deviation is 1.14, the minimum value is 3.15, and the maximum value is 8.93. The mean value of log LNER of land factor input in each province is 7.84, the standard deviation is 1.09, the minimum value is 3.84, and the maximum value is 9.85. The mean value of LNLR is 6.51, the standard deviation is 1.04, the minimum value is 3.3, and the maximum value is 8.18. The mean value of LNCP is 6.11, the standard deviation is 2.11, the minimum value is − 4.61, and the maximum value is 9.5. The mean value of LNCP_ER is − 1.73, the standard deviation is 2.08, the minimum value is − 13.15, and the maximum value is 1.24. The mean value of LNCP_ER2 is 7.34, the standard deviation is 17.82, the minimum value is 0, and the maximum value is 172.86. The mean value of LNCP_LR is − 0.13, the standard deviation is 1.7, the minimum value is − 9.55, and the maximum value is 2.53.

Table 4. Regression Result

	Overall Data		1985-2010		2011-2020	
dc	4.124**	0.643**	2.927**	0.565**	0.959**	0.264**
	(0.442)	(0.144)	(0.288)	(0.131)	(0.113)	(0.0976)
Province		control		control		control
Year		control		control		control
Constant	4.056**	-1.557**	5.365**	7.279**	7.269**	10.56**

	(0.248)	(0.307)	(0.344)	(0.132)	(0.416)	(0.139)

As shown in Table 4, columns 2-3 show the regression results of all data, columns 4-5 show the regression results from 1985 to 2010, and the last two show the regression results from 2011 to 2020. The regression coefficient of dc in column 2 is 4.124, which is significant at the 1% level. This shows that the establishment of the Big Data Bureau has a role in promoting technological progress and the application of technology in the process of increasing grain output. The regression coefficient of dc in column 3 is 0.643, which is significant at the 1% level. This shows that even after controlling fixed effects such as province and year, the promotion effect of big data technology is still significant. As stated by Jiang et al. (2012), since the reform, the institutional barriers restricting agricultural development have been removed, agricultural productivity has been greatly activated, agricultural economy has continued to develop, and grain output has continued to increase. In 1978, China's total agricultural output value was 111.8 billion yuan, and in 2010, it rose to 3.693.3 billion yuan, an increase of 33.03 times, with an average annual growth rate of 11.54%. In 1978, China's grain output was 304,765,000 tons, and in 2010, it reached 546,477,000 tons, an increase of 1.79 times, with an average annual growth rate of 1.84%. Moreover, the period from 1949 to 2020 has a large time span, during which China's relevant policies have been adjusted to varying degrees. The results show that the conclusions of this paper are robust.

Table 5. Regression Result of Changing the Base Period

	1985-2010		2011-2020	
dc	2.872***	0.554***	0.998***	0.275***
	(0.282)	(0.129)	(0.118)	(0.101)
Province		control		control
Year		control		control
Constant	5.263***	7.140***	7.560***	10.99***
	(0.338)	(0.130)	(0.433)	(0.145)

Note: The figures in parentheses are robust standard deviations, and ** and * correspond to the significance level of 1% and 5%, respectively.

When doing the regression in Table 4, the base period for calculating the contribution rate of technological progress to grain output in province i in year t is 1949. Columns 1-2 show the regression results from 1985 to 2010, and the last two columns show the regression results from 2011 to 2020. The regression coefficient of dc in column 1 is 2.872, which is significant at the 1% level. This shows that the establishment of the Big Data Bureau has a role in promoting technological progress and the application of technology in the process of increasing grain output. The regression coefficient of dc in column 2 is 0.554, which is significant at the 1% level. This shows that even after controlling fixed effects such as province and year, the promotion effect of big data technology is still significant.

5 Conclusion

It is found in this paper that the regression coefficient in regression analysis (6) is positive and significant at the level of 1%. In order to ensure the reliability of the results, the conclusions of this paper are consistent after robustness tests such as analyzing samples in different periods and changing the base period of investigation. In order to control endogeneity and potential missing variables, this paper controls variables such as industry and province in the regression.

Agriculture is the basic industry of the national economy, which is related to the stability, self-reliance and social stability of the country. Maintaining the stability and security of grain production has always been an important goal of the Chinese government's agricultural policy (Zhong, 2006). The results of this paper show that the introduction of policies related to the popularization of big data technology is conducive to promoting China's grain production and stability. It is hoped that relevant provincial and municipal government departments can further introduce policies that are conducive to big data technology and scientific and technological progress in promoting grain production.

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