Faculty of Economics and Business

Insurance and Agricultural Productivity in China: The Moderating Roles of Moral Hazard and Governance

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Doctor of Philosophy
2026

Insurance and Agricultural Productivity in China: The Moderating Roles of Moral Hazard and Governance

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A thesis submitted

In fulfilment of the requirements for the degree of Doctor of Philosophy

(Economics)

Faculty of Economics and Business
UNIVERSITI MALAYSIA SARAWAK
2026

DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

……

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Date: January 2026

ACKNOWLEDGEMENT

I would like to take this opportunity to those who have contributed directly or indirectly to this thesis.

Firstly, I would like to thank and express my deepest appreciation and gratitude and respect to my main supervisor, Dr. Muhammad Asraf Abdullah. I am indebted to his excellent guidance, enthusiasm, patience and immense knowledge during the process of completing this thesis. Without my supervisor's support, I might not be able to complete this thesis. Thank you very much.

Secondly, a special thanks to my family. Words cannot express how grateful I am to my mother. Without my mother's support, care and understanding, I will never walk this far neither achieve this much. Likewise, a special acknowledgement to my other family members for their support during these years. Thank you for your endless supports that keep me going to where I am today. Thank you very much.

Thirdly, my warm and sincere thanks to my postgraduate's colleagues and my friends who supported me in writing and encouraged me to achieve my goal. I thank my fellow mates for all the encouragement and inspiration in these few years. There are too many to mention and those whom I have yet to mention but contributed to my joy, thank you.

Finally, I would like to thank the management of the Universiti Malaysia Sarawak for making it possible for me to complete my study here in Sarawak. Thank you all.

ABSTRACT

This study examines the development of agricultural insurance in China by analysing the mechanisms through which agricultural insurance influences agricultural total factor productivity (TFP). Using panel data from 31 provinces over the period 2007–2023, agricultural TFP is estimated through the DEA–Malmquist index. The results indicate clear spatial and temporal differences in TFP growth among provinces, driven jointly by technological progress and improvements in technical efficiency. To empirically assess the impact of agricultural insurance on agricultural TFP, the study incorporates two moderating variables country governance and moral hazard into the analytical framework. A baseline fixed-effects model, a GMM model, moderating-effect models, and a threshold model are employed to ensure the robustness of the findings. Both the baseline and GMM estimations consistently demonstrate that agricultural insurance significantly enhances agricultural TFP across Chinese provinces. Regarding control variables, the baseline model suggests that household income levels is conducive to TFP growth, whereas the GMM results highlight the constraining effects of disaster shocks. Analysis of moderating effects further reveals that strong country governance amplifies the positive influence of agricultural insurance on TFP, while moral hazard weakens this relationship. Additionally, the threshold model identifies a non-linear effect: once agricultural insurance development surpasses a certain level, its capacity to promote agricultural TFP becomes markedly stronger.

Keywords: Agricultural insurance, agricultural performance, agricultural productivity, country governance, moral hazard

Insurans dan Produktiviti Pertanian di China: Peranan Sederhana Bahaya Moral dan Tadbir Urus

ABSTRAK

Kajian ini mengkaji perkembangan insurans pertanian di China dengan menganalisis mekanisme di mana insurans pertanian mempengaruhi produktiviti faktor keseluruhan pertanian (TFP). Menggunakan data panel daripada 31 wilayah dalam tempoh 2007–2023, TFP pertanian dianggarkan melalui indeks DEA – Malmquist. Keputusan menunjukkan perbezaan spatial dan temporal yang jelas dalam pertumbuhan TFP antara wilayah, didorong bersama oleh kemajuan teknologi dan peningkatan dalam kecekapan teknikal. Untuk menilai secara empirikal kesan insurans pertanian terhadap TFP pertanian, kajian ini menggabungkan dua pembolehubah penyederhanaan tadbir urus negara dan bahaya moral ke dalam rangka kerja analisis. Model kesan tetap asas, model GMM, model kesan penyederhanaan dan model ambang digunakan untuk memastikan keteguhan penemuan. Kedua-dua anggaran asas dan GMM secara konsisten menunjukkan bahawa insurans pertanian meningkatkan TFP pertanian dengan ketara di seluruh wilayah China. Mengenai pembolehubah kawalan, model asas mencadangkan bahawa tahap pendapatan isi rumah adalah kondusif untuk pertumbuhan TFP, manakala keputusan GMM menyerlahkan kesan kekangan kejutan bencana. Analisis kesan penyederhanaan seterusnya mendedahkan bahawa tadbir urus negara yang kukuh menguatkan pengaruh positif insurans pertanian terhadap TFP, manakala bahaya moral melemahkan hubungan ini. Selain itu, model ambang mengenal pasti kesan bukan linear: sebaik sahaja pembangunan insurans pertanian melepasi tahap tertentu, keupayaannya untuk mempromosikan TFP pertanian menjadi lebih kuat.

Kata Kunci: *Insurans pertanian, prestasi pertanian, produktiviti pertanian, tadbir urus negara, bahaya moral*

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LIST OF ABBREVIATIONS

AGR	Agricultural
CPC	Communist Party China
CG	Country Governance
CRS	Constant Return to Scale
DEA	Data Envelopment Analysis
EC	Efficiency Change
FAO	Food and Agriculture Organization of the United Nations
FE	Fixed Effects
GMM	Generalised Method of Moments
IN	Agricultural Insurance
MH	Moral Hazard
OLS	Ordinary Least Squares
RE	Random Effects
SFA	Stochastic Frontier Analysis
TFP	Total Factor Productivity
TC	Technological Progress

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Agriculture plays a vital role in China's national economy, serving as both a foundation of food security and a key driver of rural development (FAO, 2023). Despite rapid industrialization and urbanization in recent decades, the agricultural sector continues to support the livelihoods of hundreds of millions of rural residents and remains a strategic pillar for maintaining socio-economic stability (World Bank, 2022).

The sector contributes significantly to China’s gross domestic product (GDP). As of 2023, agriculture accounted for approximately 7.2% of the national GDP (National Bureau of Statistics of China, 2024), with a particularly high share in less industrialized provinces. In addition to its GDP contribution, agriculture is a major source of employment (OECD, 2021). In 2023, around 22% of China’s total labor force remains engaged in agricultural activities, underscoring the sector’s importance in absorbing rural labor and reducing poverty (China Statistical Press, 2024).

Agriculture also plays a critical role in ensuring food security for China's population of over 1.4 billion. The nation has made remarkable progress in grain self-sufficiency, maintaining a grain output of over 650 million tons for several consecutive years (Ministry of Agriculture and Rural Affairs of China, 2024). Moreover, agricultural development has supported the expansion of related industries such as food processing, logistics, and rural finance, creating a multiplier effect on the broader economy.

As the foundation of the national economy, agriculture plays a relatively significant role in its development (Ministry of Agriculture and Rural Affairs, 2022). The additional output growth attained through technological advancement, efficient resource allocation, innovative management, and other factors under the specific conditions of various production factors is reflected in the total factor productivity of agriculture, which is a crucial indicator for assessing agricultural production efficiency (Vercammen, 2024). It is the main engine behind the realization of agricultural modernization and the advancement of sustainable agricultural growth. Improving agriculture's overall factor productivity can boost the production and quality of agricultural goods, lower production costs, and make the sector more competitive when resources are scarce. Assuring food security, raising farmers' incomes, and fostering the growth of the rural economy all depend on it (Trakem et al., 2024).

Agricultural insurance is a crucial component among the many variables affecting agriculture's overall factor productivity. Market and natural risks are the two main challenges to agricultural output. On the one hand, frequent natural disasters such as droughts, floods, typhoons, pests, and diseases seriously affect the growth and harvest of crops, causing significant fluctuations in output and even total crop failure. On the other hand, the instability of agricultural product market prices makes it difficult for farmers to accurately predict their income, increasing the uncertainty of production decisions. In addition to causing farmers to suffer immediate financial losses, these risks impede the steady growth of agricultural output and the efficient distribution of production inputs, which stifles the increase in total factor productivity in agriculture (Prokopchuk et al., 2024).

Agricultural insurance, as an effective risk management tool, can provide risk protection for agricultural production. Through the stipulations in the insurance contract, farmers can receive corresponding economic compensation when they suffer losses due to natural disasters or price fluctuations. This ensures the continuity and stability of agricultural production by mitigating the negative effects of risk shocks on it to a certain degree (Liu et al., 2024). However, agricultural insurance also serves other purposes, such as encouraging technical innovation in agriculture and improving resource allocation, which can tangentially boost agricultural total factor output.

Moral hazard refers to a situation where, in the presence of information asymmetry, one party, not having to bear the full consequences or costs of certain risks, changes its original behavior by taking on more risks or reducing effort, thereby harming the interests of the other party (Arrow, 1963). In the context of agricultural insurance, moral hazard manifests as farmers altering their production behaviors after obtaining insurance coverage, such as reducing input investment, lowering management intensity, or relaxing risk prevention measures, which ultimately increases agricultural production risks (Smith & Goodwin, 1996). Due to the difficulty for insurance companies to observe farmers' production effort and risk management behaviors in real time, information asymmetry provides insured farmers with incentives to engage in opportunistic behavior, thereby undermining the efficiency of the insurance system and adversely affecting agricultural production performance (Goodwin & Smith, 2013).

However, because of China's enormous size, there are notable variations in the natural conditions, economic growth, agricultural production structure, and level of agricultural insurance development across different provinces. Depending on the province, the impacts and characteristics of agricultural insurance on the overall factor productivity

of agriculture may vary. In order to improve agricultural insurance policies, increase the effectiveness and targeting of agricultural insurance, fully utilize the promoting role of agricultural insurance on the total factor productivity of agriculture, and promote the high-quality development of agriculture in China, it is crucial to conduct in-depth research on the influence of agricultural insurance in each province on the total factor productivity of agriculture, revealing the mechanism of its effect and regional differences.

1.2 Roles of Agricultural Sector in China

Agriculture, as the foundation of the national economy, plays an irreplaceable role in the development process of China and all provinces. From its significant contribution to GDP, to absorbing a large number of people for employment, and to the continuous improvement of total factor productivity, the influence of agriculture runs through all aspects of the economy and society.

In 2023, the added value of agriculture and related industries in China reached 19,853.4 billion yuan, accounting for 15.34% of the country's GDP. This data highlights the significant position of agriculture in the national economic landscape (China Statistical Yearbook, 2024). Agriculture not only contributes to GDP through the direct output of agriculture, forestry, animal husbandry, and fishery, but also the development of related industries such as agricultural product processing and circulation further expands the scope of the agricultural economy.

In terms of GDP of each province, the contribution of agriculture is equally significant. As highlighted in Table 1.1, the proportion of agriculture share of GDP for each province in China generally shows a downward trend. The average growth rate in almost

all regions is negative, indicating that the proportion of agriculture is decreasing year by year. The only exception is Heilongjiang Province, where the proportion of agriculture has risen from 12.4% in 2005 to 22.2% in 2023, with an average growth rate of 12%. In economically developed regions such as Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, and Guangdong, the proportion of agriculture is extremely low (generally below 5% in 2023), and the decline rate is relatively fast. The economic structure is rapidly transforming towards the service industry, and the importance of agriculture in the economy has significantly decreased.

The proportion of agriculture in regions such as Hebei, Inner Mongolia, Jilin, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Gansu, Qinghai, and Xinjiang is relatively high (mostly above 10% in 2023), but it also shows a downward trend with a relatively slow decline. Agriculture remains an important economic pillar, but the acceleration of industrialization and urbanization has led to a gradual decrease in the proportion of agriculture. The proportion of agriculture in Heilongjiang Province has risen significantly, being the only exception in the country. The reason is that Heilongjiang is an important grain production base in China (such as soybeans and corn), and agricultural modernization and scale-up may have driven the growth of agricultural output value. Meanwhile, the relatively lagging development of industry or services has led to an increase in the proportion of agriculture instead of a decrease. China as a whole is transforming from an agricultural country to an industrial and service country (Shao, 2025).

Table 1.1: GDP Share of Agriculture by Province in China (2005-2023)

Region	2005	2010	2015	2020	2021	2022	2023	Average Growth Rate
Beijing	1.4%	0.90%	0.60%	0.30%	0.30%	0.30%	0.20%	-25.40%
Tianjin	3.0%	1.60%	1.30%	1.50%	1.40%	1.70%	1.60%	-6.86%
Hebei	14.9%	12.60%	11.50%	10.70%	10%	10.40%	10.20%	-5.93%
Shanxi	6.3%	6%	6.10%	5.40%	5.70%	5.20%	5.40%	-2.32%
Inner Mongolia	15.1%	9.40%	9.10%	11.70%	10.80%	11.50%	11.10%	-2.84%
Liaoning	11.0%	8.80%	8.30%	9.10%	8.90%	9%	8.80%	-3.22%
Jilin	17.3%	12.10%	11.40%	12.60%	11.70%	12.90%	12.20%	-4.60%
Heilong Jiang	12.4%	12.60%	17.50%	25.10%	23.30%	22.70%	22.20%	12.00%
Shanghai	0.9%	0.70%	0.40%	0.30%	0.20%	0.20%	0.20%	-20.57%
Jiangsu	8.0%	6.10%	5.70%	4.40%	4.10%	4%	4.00%	-10.40%
Zhejiang	6.6%	4.90%	4.30%	3.40%	3%	3%	2.80%	-12.89%
Anhui	18.0%	14%	11.20%	8.20%	7.80%	7.80%	7.40%	-13.17%
Fujian	12.8%	9.30%	8.20%	6.20%	5.90%	5.80%	5.90%	-11.40%
Jiangxi	17.9%	12.80%	10.60%	8.70%	7.90%	7.60%	7.60%	-12.77%
Shandong	10.6%	9.20%	7.90%	7.30%	7.30%	7.20%	7.10%	-6.28%
Henan	17.9%	14.10%	11.40%	9.70%	9.50%	9.50%	9.10%	-10.26%
Hubei	16.6%	13.40%	11.20%	9.50%	9.30%	9.30%	9.10%	-9.19%
Hunan	19.6%	14.50%	11.50%	10.10%	9.40%	9.50%	9.20%	-11.32%
Guangdong	6.4%	5%	4.60%	4.30%	4%	4.10%	4.10%	-6.81%
Guangxi	22.4%	17.50%	15.30%	16%	16.20%	16.20%	16.40%	-4.56%
Hainan	33.6%	26.10%	23.10%	20.50%	19.40%	20.80%	20.00%	-7.84%
Chongqing	15.1%	8.60%	7.30%	7.20%	6.90%	6.90%	6.90%	-10.62%
Sichuan	20.1%	14.40%	12.20%	11.40%	10.50%	10.50%	10.10%	-10.32%
Guizhou	18.6%	13.60%	15.60%	14.20%	13.90%	14.20%	13.80%	-3.99%
Yunnan	19.3%	15.30%	15.10%	14.70%	14.30%	13.90%	14.00%	-4.91%
Xizang	19.1%	13.50%	9.60%	7.90%	7.90%	8.40%	9.00%	-10.41%
Shaanxi	11.9%	9.80%	8.90%	8.70%	8.10%	7.90%	7.80%	-6.62%
Gansu	15.9%	14.50%	14.10%	13.30%	13.30%	13.50%	13.80%	-2.25%
Qinghai	12.0%	10%	8.60%	11.10%	10.50%	10.50%	10.20%	-1.64%
Ningxia	11.9%	9.40%	8.20%	8.60%	8.10%	8%	8.10%	-5.78%
Xinjiang	19.6%	19.80%	16.70%	14.40%	14.70%	14.10%	14.30%	-4.83%

Source: China Statistical Press (2006–2024).

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Secondly, agriculture is an important sector for absorbing labor force in China, providing employment opportunities for a large number of people. Although the proportion of agricultural employment has decreased with the advancement of industrialization and urbanization, the absolute number of agricultural employment remains substantial. In rural areas, from sowing, field management to harvesting, each stage of agricultural production requires a large amount of labor input. At the same time, related industries such as agricultural input sales and primary processing of agricultural products also absorb a considerable number of laborers (Potapova et al., 2024).

Take Sichuan Province as an example. As a populous province, agriculture has played a significant role in absorbing labor. In 2023, the rural areas of Sichuan have 15.35 million laborers force participating in agricultural production activities such as grain cultivation, economic crop planting, and livestock breeding (China Statistical Press, 2024). Additionally, Sichuan's unique agricultural industries, such as citrus cultivation and tea production, have formed a complete industrial chain from planting to picking and processing, providing abundant job opportunities for local farmers. Some poverty-stricken areas have achieved poverty alleviation and income growth by developing characteristic agricultural industries, making agricultural employment a key approach to addressing rural employment and poverty issues (Liao et al., 2024).

China's agricultural development in all of its provinces contributes significantly to GDP and creates jobs in the sector. To provide a stronger basis for the long-term growth of the economy and society, the government should keep supporting agriculture, encouraging the modernization of agricultural sectors, increasing the efficiency of agricultural production, and facilitating the integration of agriculture with other sectors.

1.3 Agricultural Sector Productivity in China

The primary motivation behind agricultural modernization is the increase in total factor production. One important metric for assessing agricultural production efficiency is agricultural total factor productivity, which represents the extra production efficiency attained when the input levels of different production components remain fixed (Spolador et al., 2024). China has taken a number of actions in recent years to enhance the structure of agricultural production and guarantee a continuous rise in the level of total factor productivity in agriculture (Lu, 2023).

As shown in Table 1.2, Zhang (2024) computed China's agricultural total factor productivity from 2005 to 2022. Notably, the highest growth was observed in 2019 – 2020 (1.228), while the lowest was in 2005 – 2006 (0.987), indicating a brief decline in productivity. Overall, the average TFP growth rate between 2005 and 2022 was 1.099, suggesting a generally upward trend in China's agricultural productivity during this period, with significant advancements after 2017. By conducting a comparative analysis with the research of other scholars, it was found that the total factor productivity of agriculture in China exhibits the following characteristics.

China's agricultural TFP level is steadily rising, primarily due to advancements in technology. Based on data from 2001 to 2019, Wang (2024) estimated that the annual average growth rate of the national agricultural TFP was 8.5%, while the annual average growth rate of technological progress was 8.3%. This is significantly higher than the technical efficiency growth rate of 2%, suggesting that technological advancement is the primary driver of China's agricultural TFP improvement. Meng (2024) and He (2024) also support this conclusion, measuring the national agricultural TFP annual growth rates at

approximately 9.3% and 9.4%, respectively. The impact of technological progress on TFP is significant, while technical efficiency remains relatively stable or improves slowly.

Table 1.2: China's Agricultural TFP Change from 2005 To 2022

Year	TFP Change
2004-2005	1.031
2005-2006	0.987
2006-2007	1.143
2007-2008	1.139
2008-2009	1.019
2009-2010	1.117
2010-2011	1.135
2011-2012	1.080
2012-2013	1.086
2013-2014	1.061
2014-2015	1.046
2015-2016	1.045
2016-2017	1.064
2017-2018	1.109
2018-2019	1.148
2019-2020	1.228
2020-2021	1.223
2021-2022	1.123
Average Growth Rate (2005-2022)	**1.099**

Source: Zhang (2024).

As shown in Table 1.3, over the 18-year period, the agricultural total factor productivity (TFP) of all provinces exceeded 1, indicating that production efficiency improved to varying degrees across regions. Among them, Sichuan exhibited the fastest growth in agricultural TFP, reaching 1.177, whereas Shanghai recorded the slowest growth, at 1.031, reflecting pronounced regional disparities.

Table 1.3: The provinces of China Agricultural TFP Change from 2005 To 2022

Province	TFP Change
Beijing	1.063
Tianjin	1.080
Hebei	1.090
Shanxi	1.078
Inner Mongolia	1.056
Liaoning	1.061
Jilin	1.054
Heilongjiang	1.112
Shanghai	1.031
Jiangsu	1.092
Zhejiang	1.097
Anhui	1.077
Fujian	1.105
Jiangxi	1.090
Shandong	1.127
Henan	1.092
Hubei	1.083
Hunan	1.084
Guangdong	1.080
Guangxi	1.076
Hainan	1.081
Chongqing	1.088
Sichuan	1.177
Guizhou	1.121
Yunnan	1.085
Shanxi	1.101
Gansu	1.071
Qinghai	1.112
Ningxia	1.118
Xinjiang	1.075
Average Growth Rate (2005-2022)	**1.088**

Source: Zhang (2024).

These findings are broadly consistent with existing studies, although the specific rankings differ. Wang (2024) identified Heilongjiang as the province with the highest agricultural TFP (1.037). Meng (2024) reported that Guizhou, Qinghai, and Ningxia

experienced the most rapid TFP growth, while Hainan, Liaoning, and Shanghai showed the slowest growth. Similarly, He (2024) found that Ningxia achieved the highest agricultural TFP (1.133), whereas Shanghai ranked lowest (1.025).

Overall, these results confirm the existence of substantial interprovincial differences in agricultural total factor productivity in China. In recent years, several provinces in the central and western regions have achieved notable improvements in agricultural efficiency, which may be closely associated with enhanced policy support, infrastructure development, and the diffusion of agricultural technologies.

In summary, China's total factor productivity in agriculture has steadily improved over the past two decades, with technological advancements being the main driving force behind this growth. However, uneven development across regions and slow improvements in technical efficiency remain core issues constraining the sustainable development of agriculture. In the future, efforts should focus on enhancing the conversion of agricultural technology, optimizing regional development strategies, and promoting green agriculture to comprehensively improve agricultural production efficiency and sustainability.

1.4 Food Security

In 2024, the number of people facing severe food insecurity and malnourished children worldwide exceeded 295 million, an increase of nearly 14 million compared to 2023. The number of people facing “catastrophic” hunger reached a record high (World Food Programme [WFP], 2025). Meanwhile, the second goal of the United Nations Sustainable Development Goals (Zero Hunger) proposes to eliminate hunger, achieve food security, improve nutritional status, and promote sustainable agriculture. Food security is

of vital importance to the entire world, and it is even more crucial for China, a country with a population of 1.4 billion. The Communist Party of China and the Chinese government have repeatedly emphasized over the past two years that safeguarding food security is of vital importance and that the Chinese people's rice bowls must always be firmly held in their own hands.

As shown in Table 1.4, China's cereal import dependency ratio increased from 1.6% in 2005 to 6.9% in 2020, indicating an increase in domestic grain demand in China. The cereal import dependency ratio in Asia increased from 8.3% in 2005 to 11.8% in 2020, indicating a decline in Asia's self-sufficiency capacity in food and the need to meet grain demands through imports. The world cereal import dependency ratio was -0.6%, 7.2% and 0.7% in 2005, 2010, and 2020 respectively. It can be seen that the cereal import fluctuated sharply.

China's cereal import dependency ratio is lower than the Asian average, but the relatively fast growth rate requires vigilance to avoid excessive reliance on cereal imports to meet domestic demand. The cereal import dependency ratio in Asia has been continuously increasing, and the overall external dependence has intensified (Jiao, 2025). The per capita food supply variability in China dropped from 21 kcal in 2000 to 13 kcal in 2010, indicating an improvement in the stability of the food supply chain. However, in 2020, the per capita food supply variability rebounded to 24 kcal; The per capita food supply variability in Asia has significantly improved. The per capita food supply variability has dropped from 25 kcal in 2000 to 5 kcal in 2023; The variability of the world per capita food supply chain has dropped from 14 kcal in 2000 to 3 kcal in 2023, reflecting a relatively high efficiency in world food distribution. Fluctuations have occurred in China's food supply chain, while the trends of food supply chains in Asia and globally are positive.

Table 1.4: China's Food Security Indicators (2000-2023)

Indicators	China(%)					Asia(%)					World(%)				
	2000	2005	2010	2020	2023	2000	2005	2010	2020	2023	2000	2005	2010	2020	2023
Cereal import dependency ratio (percent) (3-year average)	*X	1.6	2	6.9	*X	*X	8.3	9.5	11.8	*X	*X	-0.6	7.2	0.7	*X
Per capita food supply variability (kcal/cap/day)	21	19	13	24	22	25	21	15	6	5	14	11	10	4	3
Percentage of children under 5 years of age who are stunted (modelled estimates) (percent)	19.9	13.2	8.9	5.1	*X	37.1	34.5	30.3	22.8	*X	33	31.1	27.9	22.7	*X
Minimum dietary energy requirement (kcal/cap/day)	1865	1890	1892	1885	1897	1786	1806	1816	1826	1834	1803	1817	1823	1828	1834
Average dietary energy requirement (kcal/cap/day)	2419	2453	2455	2440	2457	2309	2337	2350	2362	2372	2332	2351	2359	2365	2372

*Note: X = data is not available

Source: Department of Statistics, FAO, 2000-2023.

The percentage of children under 5 years of age who are stunted in China has dropped significantly from 19.9% in 2000 to 5.1% in 2020, achieving remarkable results, which is attributed to China's poverty alleviation policies (Li & Pei, 2024). Although the rate of stunted growth among children under the age of five in Asia dropped from 37.1% in 2000 to 22.8% in 2020, it is still higher than that in China, reflecting the imbalance in regional development. The world rate of stunted growth among children under the age of five is similar to the trend in Asia, dropping from 33% in 2000 to 22.7% in 2020. However, the rate of decline in China far exceeds the world average.

The minimum dietary energy requirement in China has increased from 1,865 kcal in 2000 to 1,897 kcal in 2023, slightly higher than the minimum dietary capacity requirements in Asia and world. The average dietary capacity requirement in China has increased from 2,419 kcal in 2000 to 2,457 kcal in 2023, significantly higher than the average dietary capacity requirements in Asia and globally. With the development of China's economy and the improvement of living standards, the demand for dietary capacity in China has also increased accordingly (Shai & Cai, 2025).

As illustrated in Table 1.5, from 2015 to 2023, China's food trade has been in a deficit, and the deficit is getting larger and larger. Food imports in 2023 are more than three times what they were in 2015. Meat, dairy, fruit and grains are imported far more than they are exported. Only vegetable exports far exceed imports. In 2015, the food import and export deficit were 21.649 billion yuan, and in 2023, the food import and export deficit reached 460.462 billion yuan, which increased by 21.27 times. To sum up, the scale of China's annual food imports is far greater than the scale of exports, and the demand for food imports is still increasing (Zhu & Gao, 2025).

China still has to import a lot of food from overseas each year to meet the consumption needs of its people, even if the table indicates that the country's food security problem has been progressively resolved since 2010. The connection between grain supply and demand in China will continue to be closely balanced for a long time since the country's grain output has reached a point where it can no longer grow (Chen, 2023). The speed of grain production is obviously lower than that of grain consumption. At the same time, the process of urbanization has accelerated, a large number of farmers have abandoned their farmland and moved to cities, and the consumption demand for commercial grain is growing, coupled with the widespread waste of food in cities, further increasing the potential risk of tight food supply and demand (Zhang, 2023).

Under the basic national conditions of limited available land and water resources, there is limited space to make new breakthroughs in grain output by expanding cultivated land area and improving grain production intensity, and it is no longer easy to continue to maintain rapid grain increase. From the perspective of international development, the 100-year change and the global epidemic have increased the risk of uncertainty in the supply of international food trade, and many governments have implemented food inventory plans and restricted food exports (Deniz & Megan, 2024). Relying on imports of foreign food to alleviate the tight domestic food supply and demand in the future is not the best solution, and it is still necessary to use their own food production as an important security support. The tight balance between food supply and demand will reduce the ability of countries and regions to cope with emergencies such as public security incidents and major natural disasters, and even have a relatively negative impact on social stability.

Table 1.5: China: Food Trade Balance, 2015-2023 (RMB 100 million yuan)

Item	2015	2020	2021	2022	2023
Exports	**1981.39**	**2222.06**	**2098.15**	**2217.93**	**2279.42**
Live animals	37.16	41.52	36.23	36.41	34.89
Meat and Meat Preparations	65.57	49.21	56.35	66.26	70.30
Fish, Crustaceans, Mollusc & Preparations thereof	828.12	741.25	712.03	814.66	732.96
Dairy Products	37.62	39.97	40.06	47.38	52.92
Other animal Products	109.89	126.79	126.55	135.13	122.36
Vegetables	560.43	670.21	648.08	677.60	774.29
Fruits	322.55	486.29	409.25	368.91	419.00
Cereal	20.05	66.83	69.60	71.59	72.68
Imports	**2197.88**	**5175.44**	**6195.34**	**6752.86**	**6884.04**
Live animals	34.09	43.92	60.96	59.65	33.06
Meat and Meat Preparations	423.17	2099.26	2042.09	2062.94	1877.42
Fish, Crustaceans, Mollusc & Preparations thereof	393.57	857.44	892.19	1256.55	1317.49
Dairy Products	204.85	504.32	626.79	632.50	564.01
Other animal Products	28.96	52.79	67.74	90.10	92.69
Vegetables	161.88	135.59	184.63	256.59	235.38
Fruits	372.26	838.80	1029.82	1109.52	1323.25
Cereal	579.11	643.33	1291.12	1285.00	1440.74
Trade Balance	**-216.49**	**-2953.39**	**-4097.19**	**-4534.93**	**-4604.62**

Source: China's General Administration of Customs (2015-2023).

1.5 Food Production Performance in China

China is a major grain producer in the world. In 2023, the total national grain output reached 695.41 billion kilograms, an increase of 8.88 billion kilograms over the previous year, representing a growth of 1.3%. The per capita grain was 493 kilograms per person. The annual grain output set a new historical high and remained above 650 billion kilograms for nine consecutive years (Ministry of Agriculture and Rural Affairs of China, 2023). Table 1.5 shows the changes in China's major grain output from 2007 to 2023. In 2023, the output of rice, wheat and corn remained stable, reaching 206.6 million tons, 136.59 million tons and 288.84 million tons respectively. Among the total meat production, beef, mutton and poultry have steadily increased, reaching 7.53 million tons, 5.31 million tons and 25.63 million tons respectively in 2023. However, pork production was affected by African swine fever, dropping significantly in 2019 and 2020, and gradually recovered in 2021, reaching 52.96 million tons. To meet the food demands of the people, the output of aquatic products has been continuously expanding from 47.48 million tons in 2007 to 71.16 million tons in 2023.

China has made strides in grain production since the formation of the People's Republic of China and has progressively moved into a new phase of stable and high-yield production (Yang et al, 2025). The issue of people's access to food and clothing has been resolved, and a solid base for total grain security and fundamental grain self-sufficiency has been established (Liu 2024). The lack of momentum in China's grain production growth in the new era, however, is becoming more apparent when looking at the growth rate of grain production.

Table 1.6: Production of main food in China, 2007-2023 (10,000 tons)

Year	Output of the Three Main Food Crops			Total Meat				Total Aquatic Product
	Rice	Wheat	Maize	Pork	Beef	Mutton	Poultry Meat	
2007	18638	10949	15512	4287.8	613.4	382.6	1447.6	4747.5
2008	19261	11290	17212	4620.5	613.2	380.3	1533.6	4895.6
2009	19620	11580	17326	4890.8	635.5	389.4	1594.9	5116.4
2010	19723	11609	19075	5071.2	653.1	398.9	1656.1	5373
2011	20288	11857	21132	5053.1	647.5	393.1	1708.8	5603.2
2012	20653	12247	22956	5443.5	614.7	404.5	1878.9	5502.1
2013	20629	12364	24845	5493	673.2	408.1	1798.4	5744.2
2014	20961	12824	24976	5671.4	689.2	428.2	1750.7	6001.9
2015	21214	13256	26499	5645.4	616.9	439.9	1919.5	6211
2016	21109	13319	26361	5425.5	616.9	460.3	2001.7	6379.5
2017	21268	13424	25907	5451.8	634.6	471.1	1981.7	6445.3
2018	21213	13144	25717	5403.7	644.1	475.1	1993.7	6457.7
2019	20961	13360	26078	4255.3	667.3	487.5	2238.6	6480.4
2020	21186	13425	26067	4113.3	672.4	492.3	2361.1	6549
2021	21284	13694	27255	5295.9	697.5	514.1	2379.9	6690.3
2022	20850	13772	27720	5541.4	718.3	524.5	2442.6	6865.9
2023	20660	13659	28884	5794.3	752.7	531.3	2562.7	7116.2
Average Growth Rate (2007-2023)	0.66%	1.40%	4.05%	2.34%	1.38%	2.09%	3.73%	2.58%

Source: China Statistical Press (2008-2024).

From Table 1.6, with an average growth rate of 0.66% from 2007 to 2023, rice has the lowest growth rate of any grain produced. The average growth rate of wheat is 1.40%, whereas the average growth rate of maize, the grain with the highest growth rate, is 4.05%. Pork, beef, and mutton grew at average rates of 2.34%, 1.38%, and 2.09%, respectively,

while poultry meat grew at the fastest rate, 3.73%. Aquatic products grew at an average rate of 2.58%. China's total grain production increased from 100 million tons to 200 million tons in 17 years (1949-1966), from 200 million tons to 300 million tons in 12 years (1966-1978), from 300 million tons to 400 million tons in only 6 years (1978-1984), from 400 million tons to 500 million tons in 12 years (1984-1996), and it took 16 years (1996-2012) to surpass 600 million tons; In 2023, it exceeded 690 million tons (Luo et al, 2023).

China's total grain production increase has experienced a slow - accelerate - slow production process, especially in the new stage of high yield, grain output growth rate continues to decline, the growth momentum gradually weakened. China's grain production has reached a bottleneck point with rising output in the new era (Wu et al, 2024).

From Table 1.7, excluding Beijing, Zhejiang, Fujian, Guangdong, Guangxi, Hainan, Chongqing and Guizhou, the average growth rate of grain production in other provinces is positive, and grain production is increasing year by year. The negative growth of grain output in Beijing is due to the accelerated urbanization process and the occupation of a large amount of cultivated land by urban construction. The negative growth of grain in Zhejiang, Fujian, Guangdong, Guangxi and Hainan is due to the transformation of agricultural structure. These provinces are more inclined towards cash crops (such as fruits and tea), resulting in a reduction in the area of grain cultivation.

Table 1.7: Grain Production in China by Provinces, 2005-2023 (10,000 tons)

Region	2005	2010	2012	2015	2020	2021	2022	2023	Average Growth Rate
Beijing	94.9	115.7	113.8	62.6	30.5	37.8	45.4	47.8	-3.81%
Tianjin	137.5	160.6	163.6	184.5	228.2	249.9	256.2	255.7	9.57%
Hebei	2598.6	3121	3442.6	3602.2	3795.9	3825.1	3865.1	3809.9	5.83%
Shanxi	978	1107.5	1309.4	1314	1424.3	1421.2	1464.3	1478.1	6.28%
Inner Mongolia	1662.2	2344.3	2739.8	3292.6	3664.1	3840.3	3900.6	3957.8	13.89%
Liaoning	1745.8	1804	2175	2186.6	2338.8	2538.7	2484.5	2563.4	5.85%
Jilin	2581.2	2790.7	3450.2	3974.1	3803.2	4039.2	4080.8	4186.5	7.49%
Heilong Jiang	3092	5632.9	6598.6	7615.8	7540.8	7867.7	7763.1	7788.2	16.73%
Shanghai	105.4	132.1	136	125.4	91.4	94	95.6	101.9	0.64%
Jiangsu	2834.6	3285	3431.6	3594.7	3729.1	3746.1	3769.1	3797.7	4.38%
Zhejiang	814.7	686.2	648.2	584	605.7	620.9	621	638.8	-3.16%
Anhui	2605.3	3207.7	3542.9	4077.2	4019.2	4087.6	4100.1	4150.8	7.21%
Fujian	715.2	584.6	547.3	500	502.3	506.4	508.7	511	-4.44%
Jiangxi	1757	1989.4	2140.6	2235.6	2163.9	2192.3	2151.9	2198.3	3.38%
Shan Dong	3917.4	4502.8	4815.8	5153.1	5446.8	5500.7	5543.8	5655.3	5.48%
Henan	4582	5581.8	5898.4	6470.2	6825.8	6544.2	6789.4	6624.3	5.70%
Hubei	2177.4	2304.3	2485.1	2914.8	2727.4	2764.3	2741.1	2777	3.77%
Hunan	2678.6	2881.6	3061.9	3094.2	3015.1	3074.4	3018	3068	2.02%
Guang Dong	1395	1249.1	1295.7	1211.7	1267.6	1279.9	1291.5	1285.2	-1.03%
Guang Xi	1487.3	1372.1	1426.3	1433.2	1370	1386.5	1393.1	1395.4	-0.84%
Hainan	153	166.5	178.1	154.5	145.5	146	146.6	147	-0.32%
Chong Qing	1168.2	1080.6	1060.5	1051	1081.4	1092.8	1072.8	1095.9	-0.85%
Sichuan	3211.1	3182.8	3271.3	3394.6	3527.4	3582.1	3510.5	3593.8	1.64%
Guizhou	1152.1	1079.4	1161.7	1210.6	1057.6	1094.9	1114.6	1119.7	-0.19%
Yunnan	1514.9	1501.6	1687.3	1791.3	1895.9	1930.3	1958	1974	3.94%
Xizang	93.4	91.2	94.9	100.6	102.9	106.2	107.3	108.9	2.25%
Shaanxi	1043	1186	1255.9	1204.7	1274.8	1270.4	1297.9	1323.7	3.59%
Gansu	836.9	948.8	1096	1154.6	1202.2	1231.5	1265	1272.9	6.31%
Qinghai	93.3	102.2	101.7	104	107.4	109.1	107.3	116.2	3.26%
Ningxia	299.8	356.4	375	372.6	380.5	368.4	375.8	378.8	3.60%
Xinjiang	876.6	1362.4	1517.4	1895.3	1583.4	1735.8	1813.5	2119.2	15.17%

Source: Ministry of Agriculture and Rural Affairs of China 2024.

The negative growth of grain output in Chongqing and Guizhou is due to the severe population outflow, especially among young people, who tend to go to the developed coastal provinces, resulting in a shortage of agricultural labor force and dampening the enthusiasm for grain production (Wang, 2025). These included Inner Mongolia, Heilongjiang, and Xinjiang, where the average growth rate of grain production exceeded 10%; Tianjin, Hebei, Shanxi, Liaoning, Jilin, Anhui, Shandong, Henan, and Gansu, where the average growth rate of grain production exceeded 5%; and other provinces, where the average growth rate of grain production was also rising annually, but less than 5%. Major grain provinces include Hebei, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Shandong, Henan, and Hubei. The 1.41 billion inhabitants of China are guaranteed food security by the grain production of the provinces.

1.6 Farming Challenges

In the process of comprehensively promoting rural revitalization and accelerating the building of a strong agricultural country, China's agricultural development is confronted with numerous challenges. Among them, the intensification of natural disasters caused by climate change and the aging of agricultural practitioners are particularly prominent.

The impacts brought about by global climate change are profoundly altering the environment for agricultural production, and the occurrence of natural disasters is becoming increasingly frequent and severe. As can be seen from Table 1.8, the area of crops affected by natural disasters in 1990 was 38,474 thousand hectares. The highest area of crops affected by natural disasters in 2000 was 45,824 thousand hectares. The area of crops impacted by natural catastrophes has been steadily declining since 2000. In 2023,

12,072 thousand hectares of crops were still impacted by natural calamities. Natural catastrophes continue to have a significant influence on agriculture.

The area of crops affected by the drought reached its peak at 40,541 thousand hectares in 2000, and has been decreasing year by year since then. As of 2023, the area of crops affected by the drought was 6,090 thousand hectares. The area of crops affected by floods fluctuated and declined from 1990 to 2023, but rebounded by 7,190 thousand hectares in 2020, which might be related to the increase in extreme weather events.

The area of crops affected by wind and hail disasters has continued to decline. In 2023, it was only 1,175thousand hectares, reflecting the progress of agricultural disaster prevention technology in China. The freezing disaster has caused significant fluctuations in the affected area of crops. The lowest affected area was 525 thousand hectares in 2017, and it rebounded to 1,052 thousand hectares in 2020, which may be related to the abnormal temperature caused by climate change. The area of crops affected by typhoon disasters has been recorded since 2000. After 2017, the affected area decreased significantly. In 2022, the affected area was as low as 161 thousand hectares, but in 2023, it slightly increased to 348 thousand hectares. To sum up, natural disasters caused by climate change still have a huge impact on agricultural production.

Table 1.8: China: Crop disaster area from 1990 to 2023 (thousand hectares)

Indicator	1990	1995	2000	2016	2017	2018	2019	2020	2021	2022	2023
Damage area	38474	45824	54688	26221	18478	20814	19257	19958	11739	12072	10539
Drought	18175	23455	40541	9873	9875	7712	7838	5081	3426	6090	3804
Flood disaster	11804	12734	7323	8531	5415	3950	6680	7190	4760	3414	4633
Disaster caused by wind and hail	6354	4479	2307	2908	2268	2407	2228	2765	2712	1528	1175
Freezing disaster	2141	3578	2795	2885	525	3413	586	1052	379	871	519
Typhoon disaster	*X	*X	1722	2023	394	3333	1924	3863	441	161	348

*Note: X= data is not available

Source: Ministry of Agriculture and Rural Affairs of China 2024.

As shown in Figure 1.1, the sown area of crops in China remained relatively stable from 2008 to 2023 and fluctuated upward. By 2023, the total sown area of grain in China had reached 171,625 thousand hectares. The area of crops affected by natural disasters has generally shown a downward trend from 2008 to 2023. In 2023, the area of crops affected by disasters was 10,539 thousand hectares. Among them, from 2008 to 2010, the affected area of crops was relatively high. In 2009, the affected area of crops peaked at 47,214 thousand hectares. The affected area of crops decreased from 2011 to 2015, but there were still fluctuations. From 2016 to 2023, the area affected by crop disasters further decreased, reaching a minimum of 10,539 thousand hectares in 2023. To sum up, although the area affected by crop disasters has relatively decreased in recent years, the natural disasters

caused by climate change still have a huge impact on agricultural production, which requires our continuous attention.

With the advancement of agricultural technology, improvement of infrastructure, and establishment of a sound disaster prevention system, the sensitivity of Chinese agriculture to climate change has gradually decreased. During this process, agricultural insurance has effectively mitigated the impact of climate change on agricultural production by providing risk protection, promoting the adoption of adaptive technologies, enhancing the stability of production and operation, and facilitating the joint participation of the government and the market in risk management. It has thus become a crucial institutional arrangement for enhancing agricultural resilience (Chen & Gong, 2021).

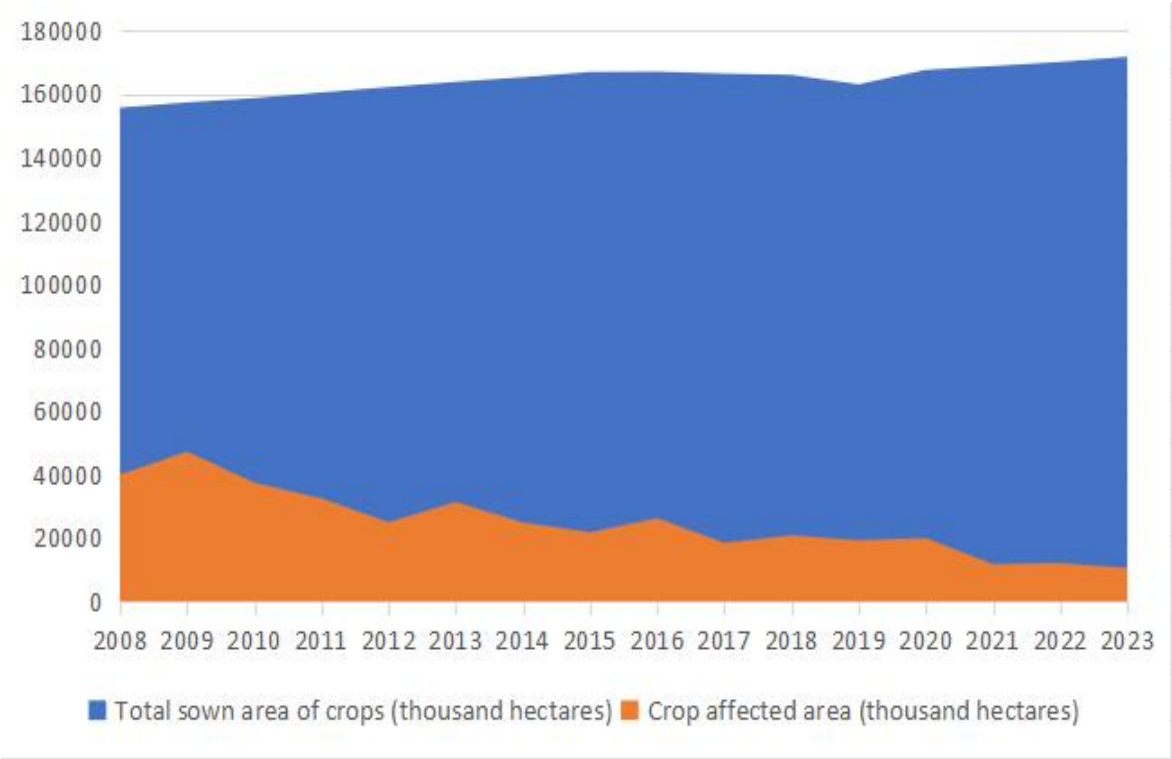

Figure 1.1: Crop Sown Area and Disaster Area in China from 2008 to 2023

The aging of agricultural practitioners in China is severe. As shown in Figure 1.2, the group with the highest proportion of agricultural practitioners is those aged over 65, reaching 53.10%, accounting for more than half, far exceeding other age groups. Secondly, the proportion of agricultural practitioners in the 60-64 age group is 28.10%. The proportion of agricultural practitioners aged 55-59 is 15.5%. The proportion of agricultural practitioners aged 50-54 is 9.2%, and the proportion of people over 50 engaged in agricultural production is relatively high. The proportions of agricultural practitioners in the lower age groups of 16-19 years old, 20-24 years old, and 25-29 years old were 3.9%, 1.7%, and 1.6% respectively. It can be seen that the proportion of agricultural practitioners under 29 years old is very low. The proportion of the middle age group aged 30 to 49 is between 2.3% and 5.4%, and the overall proportion is relatively small. To sum up, the aging of agricultural practitioners in China is severe. The majority of agricultural practitioners are over 60 years old, and the proportion of young people engaged in agricultural production is relatively low.

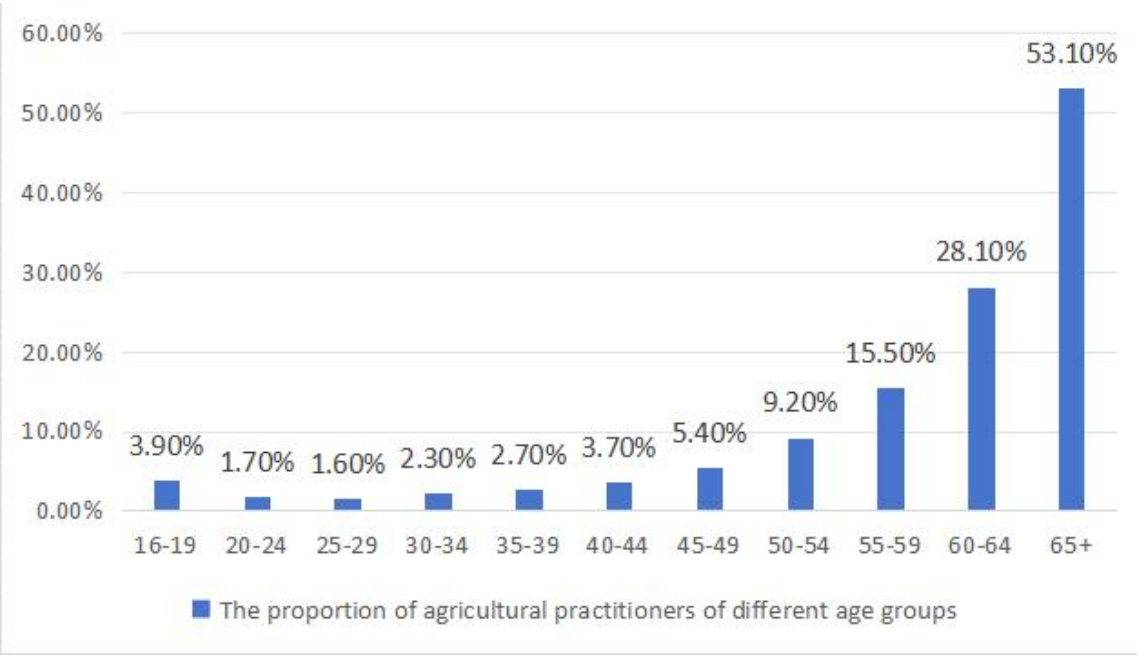

Figure 1.2: Proportion of Agricultural Practitioners of Different Age Groups in 2023

In order to guarantee the sound growth of agriculture, farm insurance was developed as a crucial component of risk distribution. Because crop insurance can shift future risks to market entities, farmers are more likely to buy it, reducing their exposure to risk as climate change worsens.

1.7 Roles of Agricultural Insurance

Since China started enacting agricultural insurance subsidy programs in 2007, more people have become aware of the vital role that agricultural insurance plays in agricultural development. In order to encourage and support the growth of agricultural insurance, the Chinese government later released a number of relevant laws, including the "Agricultural Insurance Regulations" and the "Opinions on Deepening Rural Reform and Accelerating Agricultural Modernization." In 2018, the State Council of China also clearly stated in an executive meeting that it would accelerate the advancement of agricultural insurance, enhance the ability and level of protecting farmers, and promote the modernization of agriculture. The introduction of these policies and meetings has provided strong support and guarantees for the development and promotion of agricultural insurance.

In 2022, the China Banking and Insurance Regulatory Commission issued the “Notice on Key Tasks for Banking and Insurance Industries to Fully Promote Rural Revitalization,” requiring banks and insurance institutions to integrate rural revitalization services with their own development strategies and continuously optimize the financial supply system related to agriculture. The "Guiding Opinions on Financial Support for Comprehensive Promotion of Rural Revitalization and Accelerating the Construction of a Strong Agricultural Country," jointly released in 2023 by the People's Bank of China, the

Ministry of Agriculture and Rural Affairs, and other ministries, specifically noted the need to offer financial services for grain and other important agricultural products, improve the capacity of insurance protection services, broaden the scope of agricultural insurance implementation, and further enhance specialized agricultural insurance products (He, 2024). The growth of farm insurance has steadily accelerated under the strong influence of policies, and several forms of agricultural insurance have also been widely used.

In 2023, the premium scale of agricultural insurance in China reached 141.3 billion yuan, increasing by 17.24% year-on-year. Risk coverage of 4.98 trillion yuan was provided to 164 million rural households, an increase of 9.14% year-on-year (China National Financial Regulatory Administration, 2024). The first role of agricultural insurance is to enhance farmers' ability to avoid risks. After farmers purchase agricultural insurance, insurance companies use technologies such as satellite remote sensing and unmanned aerial vehicle aerial photography, and integrate big data such as meteorology, soil, and historical yields to establish risk models for precise risk assessment, continuously improving farmers' ability to avoid risks. The second point is that when farmers suffer from natural disasters, they can obtain corresponding compensation, which stabilizes farmers' income. In 2023, the agricultural insurance payout expenditure was 110.7 billion yuan, providing sufficient guarantee for farmers' income. The third is to ensure agricultural output (China National Financial Regulatory Administration, 2024). In 2023, the coverage rate of China's three major grain insurance policies reached 72%. When farmers suffered from natural disasters, the claims payment ensured timely resumption of farming after the disaster, safeguarding China's grain output of 69.541 billion kilograms (China National Financial Regulatory Administration, 2024).

By providing financial compensation and risk diversification to farmers impacted by calamities, agricultural insurance can help stabilize agricultural productivity and promote agricultural economic growth. Economic compensation is the circumstance in which, following the purchase of agricultural insurance, the insurance company will pay the farmers directly for their production costs or a portion of their anticipated returns in the event that their insured crops is harmed by natural disasters, illnesses, or accidents. The use of the "law of large numbers" in insurance to spread out the significant losses of a small number of farmers among many policyholders is known as risk diversification.

Figure 1.3 shows that the agriculture insurance premium income in China in 2008 was 11 billion yuan, or 1.1% of the overall premium income. By the end of 2023, China's agriculture insurance premium income had expanded to 141.3 billion yuan, and its share of the country's overall premium income had risen to 2.8%.

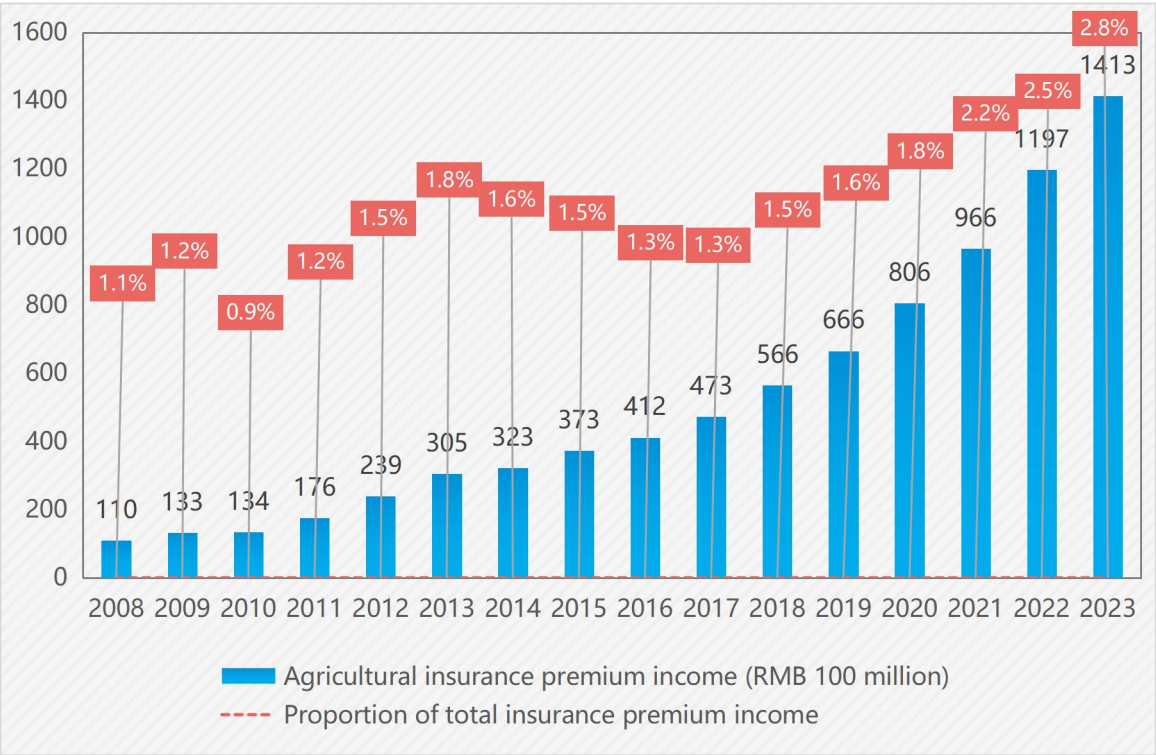

Figure 1.3: China's Agricultural Insurance Premium Income from 2008 to 2023

The development of traditional cost insurance was the primary focus during the 2008–2012 policy-based farm insurance beginning phase. The regions were mostly found in the primary areas that produced grain. In 2008, agriculture insurance premium income was 11 billion yuan; by 2012, it had grown to 23.9 billion yuan. With the extension of agricultural insurance coverage and the strengthening of subsidy programs, the premium income of agricultural insurance rose from 30.5 billion yuan in 2013 to 80.6 billion yuan in 2020. The insurance revenue of agriculture insurance grew from 96.6 billion yuan in 2021 to 141.3 billion yuan in 2023, during the high-quality development stage of the insurance industry. China's agriculture insurance market has grown by more than 10 times in size and its market share has been steadily increasing after more than a decade of expansion.

The insurance industry in China has grown quickly since reform and development, notably in recent years as people's living conditions have improved and awareness of the insurance industry has grown. A key strategy to encourage the development of agriculture in China is the use of agricultural insurance. The income from farm insurance premiums in China would be 141.3 billion Yuan in 2023 (China National Financial Regulatory Administration, 2024). All of China's provinces have implemented agricultural insurance programs that essentially cover every aspect of agricultural output, including fisheries, animal husbandry, forestry, and plantations.

Agricultural insurance can effectively manage the risks associated with agricultural production and is essential to the advancement of contemporary agriculture. In the face of moral hazard and adverse selection, agricultural insurance is a crucial tool for mitigating financial losses and safeguarding agricultural output. It also lowers agricultural chemical inputs, mitigates resource waste and pollution issues, and promotes green

agricultural production (Liu, 2024). The development of agricultural technology, the urbanization of rural migrant populations, the standardization of agricultural product markets, and the greening of agricultural output are all significantly impacted by agricultural insurance (Zheng & Ning, 2025). To a certain degree, agricultural insurance can ensure the supply of agricultural products, stabilize farmers' income, and encourage the use of technology as an agricultural support policy for risk diversification and income assurance (Liu, 2024). The overall factor productivity of agriculture is positively impacted by advancements in agricultural technology. The development of agricultural infrastructure, agricultural mechanization, and rural human capital all contribute to the positive impact of technical advancement on agricultural productivity, with the more developed a region, the larger the effect (Li, 2024). Based on the aforementioned study, it can be concluded that agricultural insurance promotes agricultural technology advancement, which in turn promotes the growth of agricultural total factor productivity. Consequently, agricultural insurance and agricultural total factor productivity are closely related.

1.8 Agricultural Insurance and Moral Hazard

The Chinese government prioritizes the development of agricultural insurance and has put in place a number of preferential policies, including financial subsidies, to better transfer agricultural risks and lessen the financial losses incurred by farmers as a result of natural disasters. The Chinese government started offering agriculture insurance premium discounts in 2007. From the original five categories of insurance to 18 types, the scope of subsidies for agricultural insurance has progressively grown to encompass nearly all sectors of agriculture, forestry, animal husbandry, and fisheries. With central and provincial financial premium subsidies making up roughly 55% of the total, the number of provinces

covered by agricultural insurance has also increased from the original six pilot provinces to the entire nation, greatly easing the financial burden on farmers who buy agricultural insurance (Lu, 2025).

The depth of agricultural insurance measures how well the agricultural economy is covered by agricultural insurance and is calculated as the ratio of premium income to total agricultural output value. The contribution of agricultural insurance to the gross value of agricultural production increases with the ratio of agricultural insurance premium depth, suggesting a higher demand for crop insurance among farmers. The ratio of agricultural insurance premium income to the number of workers in the primary industry, or the per capita premium expenditure on agricultural insurance, indicates the degree of farmer participation in agricultural insurance and is known as agricultural insurance density.

As shown in Figure 1.4 and 1.5, with the joint efforts of Chinese insurance companies and national policies, the depth and density of agricultural insurance in China have been continuously improved.

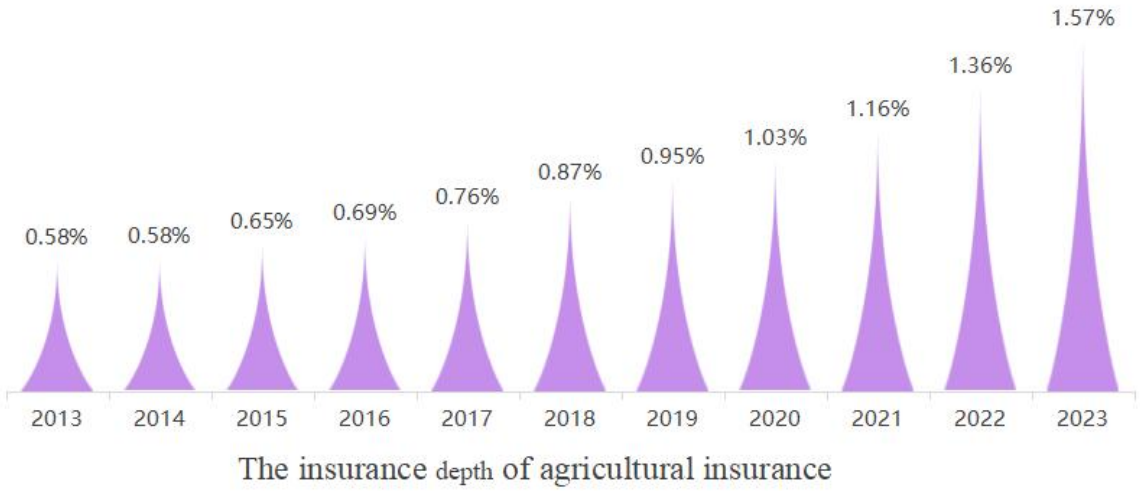

Figure 1.4: Depth of China's Agricultural Insurance from 2013 to 2023

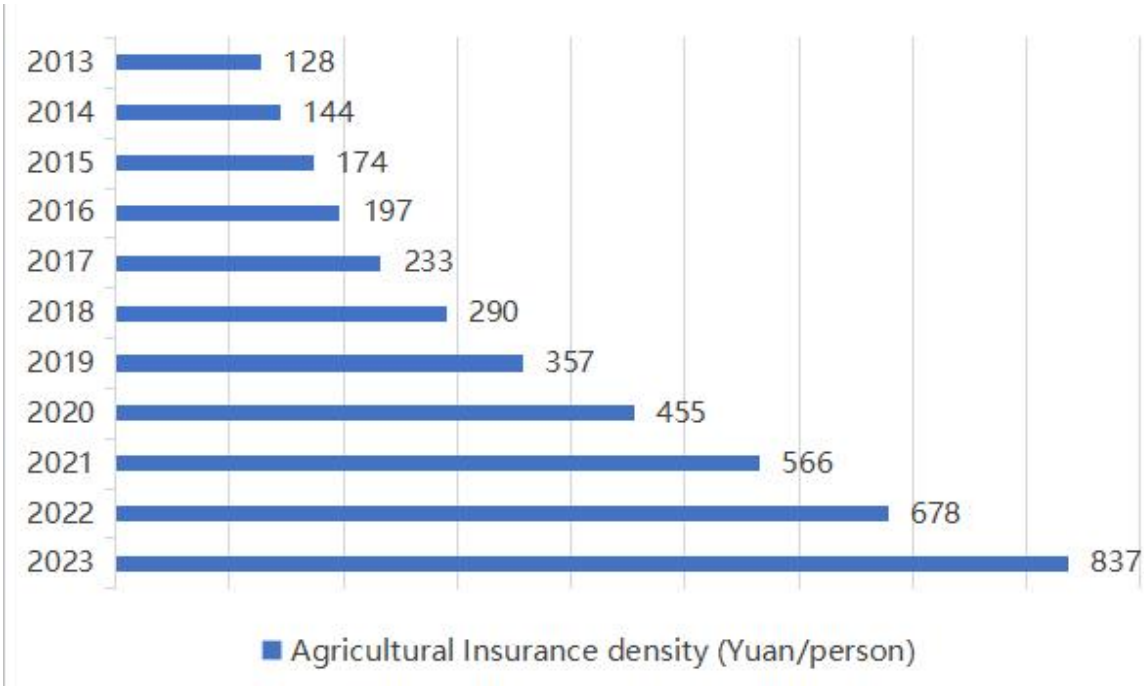

Figure 1.5: Density of Agricultural Insurance in China from 2013 to 2023

From the figures 1.4 and 1.5, the depth of Chinese agricultural insurance has expanded from 0.58% in 2013 to 1.57% in 2023, and the density of agricultural insurance has increased from 128 yuan per person in 2013 to 837 yuan per person in 2023. The rapid growth of the insurance depth and density of China's agricultural insurance reflects the increasingly important role that agricultural insurance plays in ensuring agricultural output and promoting agricultural economic development.

As shown in Figure 1.6, from 2013 to 2023, the amount of compensation and China's agricultural insurance premium income are both rising. China's agricultural insurance benefits and compensation were RMB 108.9 billion in 2023, an increase of 28.88% year over year from RMB 84.5 billion in 2022. In 2023, with the rapid growth of agricultural insurance premium income, the loss rate of agricultural insurance has increased compared with 2022, and the loss rate in 2023 is 77.07%.

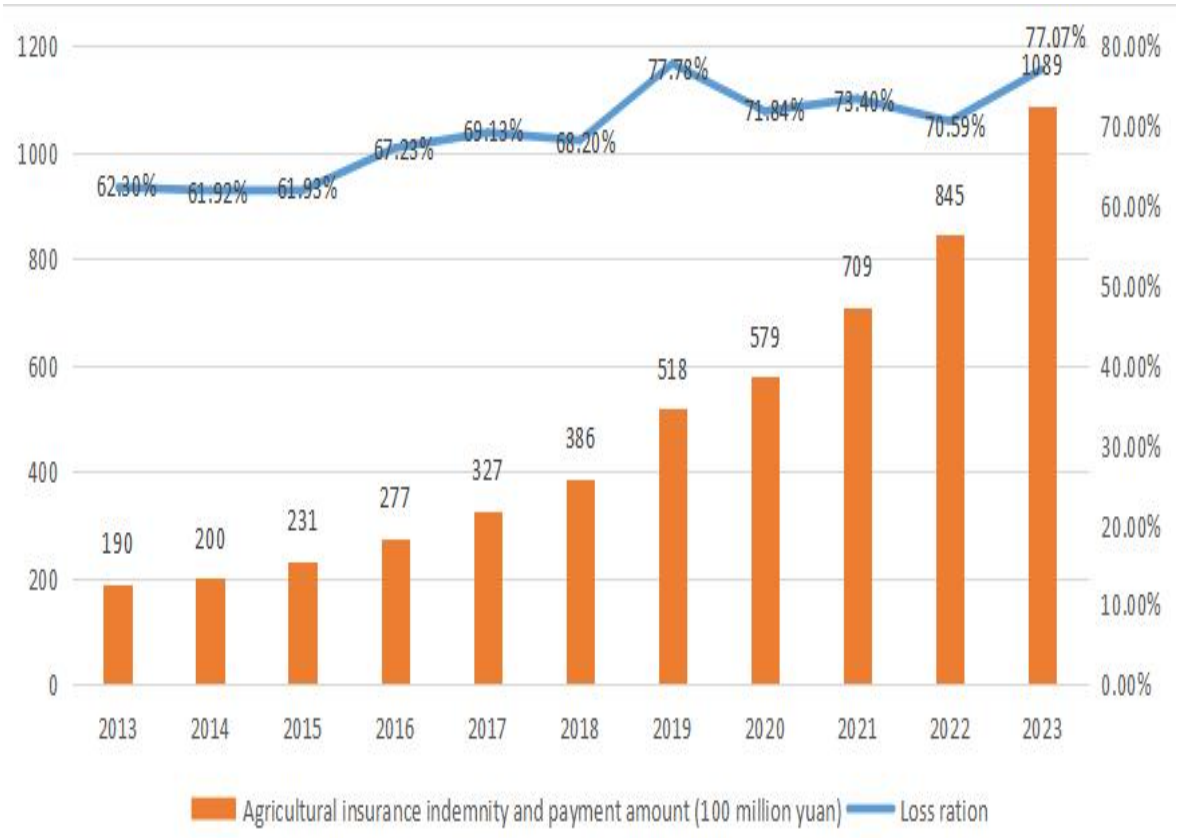

Figure 1.6: China's Agricultural Insurance Compensation, Payment Amount and Compensation Rate from 2013 To 2023

Under the encouragement of the state financial subsidy policy, the agricultural insurance in our country has achieved rapid development, but at the same time, it also causes new moral hazard problems (Yi et al., 2024). First of all, in the insurance and underwriting links, agricultural insurance generally adopts collective insurance. The basic information required by the insurance company when underwriting the insurance is mainly from the local grass-roots township (town) and group farm. Insurance companies mainly verify the authenticity of relevant information through random checking of case files, telephone return visits and other ways, and the coverage rate of field inspection is low. As a result, insurance companies have inaccurate information about the policyholders, local government organizations and the subject matter of insurance.

In addition, the lack of agricultural insurance professionals in insurance companies leads to poor underwriting quality, which leads to the rise and accumulation of moral hazard among agricultural insurance buyers, thus exaggerating the risk accidents and losses during the risk (Duan & Yang, 2024). Even fictitious risk accidents defrauding insurance companies for compensation and other incidents occur. The nature of the land involved in the subject matter of planting agricultural insurance is complex. In addition to rural collective ownership land, there are a large number of cultivated lands of other nature such as contracting of state-owned barren land and private reclamation by farmers and their circulation is frequent. The secondary circulation of land is irregular, and the contracts and certificates provided by agricultural and land departments are difficult to reflect the real situation. Such a situation is likely to induce moral hazard such as overreporting or false reporting of the subject land area, exaggerating or fabricating the amount of the subject matter of insurance by the insured party, especially the collective insurance agents of local government grass-roots organizations alone or colluding (Yuan et al., 2024).

Secondly, moral hazard and adverse selection during the duration of the agricultural insurance contract are usually caused by the applicant deliberately neglecting to perform the duties of risk prevention and risk suppression, deliberately reducing preventive measures, and the applicant reducing the prevention of diseases, pests and diseases, and possible natural disasters occurring on the subject matter of the insurance in order to reduce the cost expenditure during the insurance contract (Xiao et al., 2024). For example, the insured person reduces the spraying of pesticides, does not prevent and rescue possible or early disease of crops, and does not actively increase and manage facilities and equipment to prevent natural disasters. In terms of risk control, the moral hazard and adverse selection during the life of agricultural insurance contracts usually show that the

insured does not actively help when the risk accident occurs, and even intends to expand the loss in order to obtain more insurance payments (Shi, 2024).

There is moral hazard that cannot be completely eliminated in the economic behavior between economic entities. The subject matter of agricultural insurance is complex and diverse, the scope is large, and there are many game players in the operation of agricultural insurance. The information asymmetry in this field is often more serious than that in other insurance.

1.9 Institutions and Agricultural Development

People started to realize as civilization advanced that a conducive atmosphere for effective governance is necessary for the development of agriculture. Agricultural progress will be severely constrained if there isn't a robust governance framework, relying just on material capital investment and the adoption of new agricultural technologies. According to Barbosa (2024), it is good government institutions and policies that correlate to agricultural development, not the scarcity of natural resources or the absence of cutting-edge agricultural production technologies, that impede agricultural development.The development of healthy market competition and the realization of low transaction costs will be made possible by a good governance environment, which will also encourage the innovation of agricultural technology. This will allow agriculture to adopt new technologies as quickly as possible to increase agricultural productivity. Infrastructure, public goods, and services in rural areas are mostly provided by the government. The government also establishes macroeconomic regulations that influence agricultural productivity and investment. Government governance is essential to the growth of the rural economy.

Research on the relationship between agricultural insurance and agricultural total factor productivity should account not only for differences in natural endowments and input intensity, but also for disparities in governance quality, which play a crucial role in shaping the effectiveness of agricultural insurance (Kaufmann et al., 2011). In provinces with stronger governance capacity—characterized by effective policy implementation, transparent subsidy allocation, and robust monitoring mechanisms—agricultural insurance is more likely to enhance production efficiency by stabilizing farmers' income expectations, encouraging technology adoption, and facilitating optimal input allocation (Tang et al., 2022).

By contrast, in regions with weaker governance, deficiencies in regulatory oversight and institutional enforcement may dilute the productivity-enhancing role of agricultural insurance. Inadequate supervision can exacerbate moral hazard and adverse selection, leading insured farmers to reduce productive inputs or engage in opportunistic behavior, thereby offsetting the potential efficiency gains from insurance coverage (Cai et al., 2020). Consequently, even with similar levels of insurance development, provinces with weaker governance may experience slower growth in agricultural total factor productivity.

This governance-dependent effect helps explain why several central and western provinces have recently achieved rapid improvements in agricultural efficiency, as strengthened local governance, targeted policy support, and improved infrastructure have enhanced the productivity impacts of agricultural insurance (Zhang & Shi, 2023). Conversely, in regions where governance constraints persist, the ability of insurance mechanisms to translate risk protection into sustained productivity gains remains limited

(Kaufmann et al., 2011). The World Bank provided the six indicators of governance, which are voice and accountability, political stability and lack of violence, government effectiveness, regulatory excellence, rule of law, and control of corruption.

Table 1.9 displays data on China's country governance indicators from 2000 to 2023. The government's ability to carry out policies has improved, as evidenced by the notable improvement in government effectiveness, which went from -0.16 in 2000 to 0.68 in 2023; corruption control has improved from -0.21 in 2000 to -0.0054 in 2023, though it is still in the negative range. In terms of political stability, it is comparatively stable, staying at or near -0.5, suggesting that China's political climate is stable despite some difficulties; in terms of rule of law, it has improved from -0.52 (2000) to -0.04 (2023), demonstrating advancements in the rule of law's development. With minimal change, the regulatory quality score stays between -0.3 and -0.4; the accountability and freedom of speech scores the lowest, staying at -1.5, suggesting little improvement in these areas. To sum up, China's national government has significantly improved overall. According to Espoir et al. (2024) research, agricultural productivity is positively impacted by a high degree of governance in Africa. This article also examines the relationship between national governance and agricultural development, as supported by the aforementioned research.

Table 1.9: China's Country Governance Indicators 2000-2023

Indicators	2000	2005	2010	2015	2020	2021	2022	2023
Control of Corruption: Estimate	-0.20854871	-0.617887735	-0.570009887	-0.29992187	-0.071028143	0.030233584	0.016063672	-0.005370105
Government Effectiveness: Estimate	-0.158842877	-0.140640497	0.091844857	0.41742301	0.643971682	0.807911634	0.494212538	0.679014027
Political Stability and Absence of Violence/Terrorism: Estimate	-0.209916875	-0.501756608	-0.657060683	-0.552559674	-0.474127859	-0.516462862	-0.45127672	-0.513097048
Regulatory Quality: Estimate	-0.324955195	-0.183769479	-0.320954978	-0.354117453	-0.20264338	-0.332243532	-0.418417633	-0.356507808
Rule of Law: Estimate	-0.516117156	-0.650172889	-0.472601861	-0.4084557	-0.102505103	0.010268886	-0.042176291	-0.040129971
Voice and Accountability: Estimate	-1.384080529	-1.500785112	-1.680547476	-1.660783172	-1.656358719	-1.641274571	-1.60137105	-1.504554152

Source: World Bank (2000-2023).

1.10 Problem Statement

With a population of 1.41 billion, China faces mounting pressure to ensure long-term food security (Sun et al., 2025). Despite efforts to enhance agricultural productivity, domestic food production still falls short of demand, as reflected in the soaring food trade deficit, which reached 460.462 billion yuan in 2023—over 21 times the figure from 2015 (China's General Administration of Customs, 2024). The disparity between production and consumption has been made worse by structural problems, including dwindling arable land, disjointed farming systems, aging rural labor, and a lack of local supply of important staples like corn and soybeans (Zhou & Tian, 2023; Yu & Huang, 2022). China's food security is becoming more susceptible to geopolitical threats and fluctuations in the world market due to its growing reliance on imported grains, oilseeds, and other food items (OECD & FAO, 2023; Huang et al., 2021). Therefore, maintaining sustainable productivity growth while guaranteeing food self-reliance continues to be a crucial policy concern for China (World Bank, 2022).

Compared with other sectors and developed countries, China's agricultural productivity remains relatively low, with significant regional disparities. From 2009 to 2021, the national average growth rate of agricultural total factor productivity (TFP) was approximately 9.4%. Regions such as Ningxia achieved a high annual TFP growth rate of 13.3%, largely due to the promotion of specialty crops and targeted policy support for high-efficiency farming systems. In contrast, areas like Shanghai lagged behind at 2.5%, reflecting constraints from rapid urbanization, aging rural labor, and shrinking farmland (He, 2024; Zhou & Liu, 2022). Regionally, eastern China exhibited stronger TFP performance (3.5%) compared to central (2.69%) and western regions (2.21%), a pattern

often attributed to better agricultural infrastructure, higher mechanization levels, and more comprehensive agricultural insurance systems (Wang, 2024; Zhang & Chen, 2023). Disparities in land consolidation, uneven governmental investment, and differing capacities to adopt contemporary agricultural technologies are the main causes of regional TFP disparities, according to empirical studies (Sheng et al., 2019; Yu & Nin-Pratt, 2020). Furthermore, poor areas frequently do not have access to finance markets and high-quality extension services, which further restricts the rise of productivity (Huang et al., 2021). Therefore, closing the regional TFP gap is crucial to attaining sustainable and equitable agricultural development throughout China.

Agriculture is inherently a high-risk sector due to its strong exposure to natural conditions, biological processes, and market volatility. Agricultural risk management theory emphasizes that when production and market risks are not effectively managed, farmers tend to adopt conservative decision-making strategies, reduce long-term investment, and deviate from optimal input allocation, ultimately hindering productivity growth (Moschini & Hennessy, 2001; Tack & Yu, 2021). As a key risk-transfer instrument within the agricultural risk management framework, agricultural insurance aims to stabilize farmers' income expectations, reduce uncertainty, and reallocate production risks away from individual producers. By lowering perceived risk and income volatility, agricultural insurance relaxes farmers' risk constraints and creates incentives for greater investment in productivity-enhancing technologies and modern inputs.

From the perspective of agricultural productivity theory integrated with risk management, total factor productivity (TFP) growth reflects not only technological progress and efficiency improvements but also farmers' ability to allocate production

factors optimally under uncertainty (Coelli et al., 2005). By mitigating downside risks and smoothing income fluctuations, agricultural insurance can improve farmers' intertemporal decision-making, encourage the adoption of advanced technologies, and enhance input-use efficiency, thereby facilitating structural upgrading in agriculture and promoting TFP growth. However, agricultural risk management theory also highlights that the effectiveness of risk-transfer instruments is conditional on institutional settings and behavioral responses, implying that the productivity effects of agricultural insurance are inherently heterogeneous rather than automatic or uniform.

Agricultural risk management theory suggests that the effectiveness of insurance-based risk management instruments critically depends on governance quality. Country governance shapes the design, implementation, supervision, and enforcement of agricultural insurance policies, including subsidy allocation, loss assessment, claim verification, and the monitoring of insurer and farmer behavior (Kaufmann et al., 2011; Moschini & Hennessy, 2001). In regions with high governance quality—characterized by strong government effectiveness, sound regulatory quality, and effective control of corruption—agricultural insurance is more likely to operate as an incentive-compatible risk management tool. Effective governance reduces subsidy leakage, improves policy credibility, and ensures that indemnity payments are linked to genuine losses rather than opportunistic behavior, thereby amplifying the positive impact of agricultural insurance on agricultural total factor productivity (TFP) (Gani, 2022; Ilhan, 2022).

In contrast, weak governance undermines the risk management function of agricultural insurance by distorting policy incentives and weakening regulatory enforcement. Under such conditions, insurance subsidies may encourage rent-seeking, reduce insurers' monitoring incentives, and crowd out farmers' self-protection and risk-

prevention efforts, resulting in inefficient input allocation and diminished production efficiency (Just et al., 1999; Glauber & Guo, 2020). Consequently, the productivity-enhancing effects of agricultural insurance may be substantially weakened or even reversed. Therefore, country governance serves as a critical moderating factor that conditions whether agricultural insurance can be effectively translated into sustainable productivity gains.

Information asymmetry theory provides a fundamental explanation for the emergence of moral hazard in agricultural insurance markets. Because insurers face substantial difficulties in observing farmers ' effort levels, input choices, and risk-prevention behaviors, insured farmers may adjust their production decisions after obtaining insurance coverage (Arrow, 1963; Pauly, 1968). This principal – agent problem is particularly pronounced in agriculture due to the spatial dispersion of production activities, the stochastic nature of yields, and the high costs of monitoring on-farm behavior (Just et al., 1999; Smith & Goodwin, 1996).

From the perspective of agricultural productivity theory, moral hazard directly influences production efficiency by weakening effort incentives, distorting optimal input allocation, and increasing production risks. Empirical evidence suggests that insured farmers may reduce chemical use, labor input, or management intensity, which can undermine productivity gains expected from risk mitigation (Horowitz & Lichtenberg, 1993; Ceballos et al., 2017). When moral hazard intensifies, the risk-reducing benefits of agricultural insurance may be offset by efficiency losses, thereby attenuating or even reversing its impact on agricultural total factor productivity (TFP) (Glauber & Guo, 2020).

Conversely, when moral hazard is effectively controlled through incentive-compatible contract design, improved governance oversight, or complementary institutions

such as credit constraints and monitoring mechanisms, agricultural insurance is more likely to promote productive investment and efficiency improvements (Goodwin & Smith, 2013; Xiu & Lyu, 2020). Therefore, moral hazard should not be viewed merely as a byproduct of insurance coverage but rather as a key behavioral moderator that conditions the relationship between agricultural insurance and agricultural TFP.

Agricultural risk management theory implies that the impact of agricultural insurance on productivity may exhibit threshold effects rather than linear relationships, as the effectiveness of risk-transfer instruments depends on their scale, coverage depth, and incentive structure (Hansen, 1999; Moschini & Hennessy, 2001). At low levels of insurance development — characterized by limited coverage, low participation rates, or insufficient subsidy intensity — agricultural insurance may be ineffective in substantially reducing farmers' risk exposure, resulting in negligible or insignificant productivity effects (Tack & Yu, 2021).

As insurance development reaches a critical threshold, risk mitigation becomes sufficiently strong to relax farmers' risk constraints, encourage investment in modern inputs, facilitate technological adoption, and improve the efficiency of input allocation, thereby promoting agricultural total factor productivity (TFP) growth (Feng et al., 2021; Jin et al., 2022). This stage reflects the productivity-enhancing role of agricultural insurance as an effective risk management tool.

However, beyond an optimal threshold, excessively high insurance coverage or overly generous premium subsidies may intensify moral hazard and impose increasing fiscal burdens. Under such circumstances, farmers' effort incentives may weaken, input use may become inefficient, and opportunistic behavior may rise, ultimately reducing

production efficiency and diminishing productivity gains (Goodwin & Smith, 2013; Xiu & Lyu, 2020). This nonlinear mechanism provides a coherent theoretical explanation for the mixed and sometimes contradictory empirical findings in the existing literature and underscores the necessity of explicitly testing threshold effects when examining the productivity impacts of agricultural insurance.

Despite extensive research on agricultural insurance, few studies integrate agricultural risk management theory, agricultural productivity theory, and information asymmetry theory within a unified framework to examine how governance quality, moral hazard, and nonlinear effects jointly shape the insurance – TFP relationship. Addressing these gaps, this study investigates the impact of agricultural insurance on agricultural TFP across Chinese provinces from 2007 to 2023, while explicitly examining the moderating roles of country governance and moral hazard, as well as the presence of threshold effects in the insurance–TFP nexus.

1.11 Research Questions

i. What is the productivity level of the agricultural sector in China Provinces?

ii. What is impact of agricultural insurance on agricultural total factor productivity?

iii. Does country governance moderate the relationship between agricultural insurance and agricultural total factor productivity?

iv. Does moral hazard moderate the relationship between agricultural insurance and agricultural total factor productivity?

v. Does agricultural insurance exhibit a threshold (nonlinear) effect on agricultural total factor productivity across different stages of insurance development?

1.12 Objectives of the Study

This study emphasizes on agricultural insurance development, mainly focusing on the relationship between agricultural insurance development and agricultural productivity. This can be achieved through the following set of general objectives and specific objectives:

General Objective:

The general objective of this study is to examine the impact of agricultural insurance development on agricultural total factor productivity in China, taking into account governance quality, moral hazard, and threshold effects.

Specific Objectives:

i. To evaluate the productivity of agricultural sector in China's provinces

ii. To assess the impact of agricultural insurance on total factor productivity

iii. To examine the moderating impact of country governance on the relationship between agricultural insurance and agricultural total factor productivity

iv. To investigate the moderating impact of moral hazard on the relationship between agricultural insurance and agricultural total factor productivity

v. To study whether the impact of agricultural insurance on agricultural total factor productivity exhibits significant threshold effects across different stages of insurance development.

1.13 Scope of the Study

This study first measures agricultural total factor productivity using the DEA-Malmquist method, using data from 31 China provinces as samples. It then examines the effect of agricultural insurance on agricultural total factor productivity using fixed effcets model and GMM model. Then, the relationship between agricultural insurance and agricultural total factor productivity is studied by taking country governance and moral hazard as moderating variables. Finally, the impact of agricultural insurance on agricultural total factor productivity is investigated by taking agricultural insurance as a threshold variable.

1.14 Contribution of the Study

This study makes significant contributions from three key perspectives: empirical contributions, practical implications, and theoretical advancement.

In terms of empirical contribution, this study offers robust empirical evidence by systematically measuring the total factor productivity (TFP) of agriculture across multiple provinces in China. By decomposing TFP growth into technological progress and efficiency change, the study identifies regional differences and developmental patterns. Provinces with higher agricultural TFP were found to achieve growth primarily through both technological and efficiency improvements, whereas regions with medium or low TFP

growth relied more heavily on technological adoption, revealing weaknesses in resource management. Furthermore, the study empirically examines the impact of agricultural insurance on TFP, including the moderating roles of national governance and moral hazard. It provides new quantitative evidence on how institutional factors influence the effectiveness of agricultural insurance in promoting productivity.

For practical implication, this study provides policy-relevant insights into the role of agricultural insurance as a tool to enhance agricultural productivity. It highlights that improving national governance structures can strengthen the function of agricultural insurance, while unchecked moral hazard can hinder its effectiveness. The findings suggest that tailored insurance schemes and improved governance mechanisms can help mitigate regional disparities in agricultural productivity. In addition, the threshold effect identified in the analysis indicates that increasing investment in agricultural insurance beyond a certain level can lead to amplified productivity gains. These findings have direct implications for policymakers seeking to enhance food security, reduce regional inequality, and promote sustainable agricultural development.

As for theoretical advancement, this study expands the understanding of the relationship between agricultural insurance and total factor productivity by incorporating nonlinear and institutional perspectives. The introduction of national governance and moral hazard as moderating variables enriches the analytical framework linking policy instruments to productivity outcomes. Furthermore, the identification of a threshold effect offers a novel theoretical insight into how the effectiveness of agricultural insurance evolves with its intensity. These contributions extend existing literature on agricultural development, insurance economics, and public policy by proposing a more nuanced

mechanism through which agricultural insurance affects productivity under different governance and risk conditions.

1.15 Organization of the Study

This dissertation is structured to systematically investigate the relationship between agricultural insurance and the total factor productivity (TFP) of agriculture in China. It begins with a review of relevant literature, followed by the collection and processing of panel data from 31 provinces, the measurement of agricultural TFP, the construction of empirical models, and the development of policy recommendations based on analytical results. The main content of the study is organized into five chapters.

Chapter 1 provides the introduction to this study. It outlines the background of the study, including the status of food production and food security in China, major agricultural challenges, and the role of agricultural insurance. It further discusses the issues of moral hazard, the role of institutions in agricultural development, and articulates the research problem, questions, objectives, contributions, and the organization of the study.

Chapter 2 provides the review of literature the theoretical foundation of the study. It reviews key concepts, characteristics, and functions of agricultural insurance and agricultural productivity. The chapter also explores the theoretical mechanisms through which agricultural insurance may influence agricultural TFP, highlighting the potential contributions of agricultural insurance to China's economic and social development.

Chapter 3 introduces the empirical strategy used to examine how agricultural insurance affects agricultural total factor productivity across Chinese provinces. It covers variable selection, model design, and the construction of several econometric models.

These include the baseline model, a GMM model to address endogeneity, a moderating effect model to assess the role of country governance, and a threshold effect model to explore potential non-linear relationships. Together, these models aim to provide a comprehensive analysis of the agricultural insurance and TFP relationship.

Chapter 4 presents the empirical findings and robustness checks. It analyzes the impact of agricultural insurance on agricultural total factor productivity and further examines how country governance and moral hazard moderate this relationship. The results offer insights into both the direct effects of agricultural insurance and the threshold effect which its impact on productivity varies.

Chapter 5 summarizes the key empirical findings and provides practical policy recommendations for enhancing agricultural total factor productivity through the development of agricultural insurance. It emphasizes how targeted insurance policies can help sustainable agricultural expansion when they are backed by sound governance. The chapter ends with recommendations for additional study and policy development to boost China's agricultural productivity and resilience.

1.16 Chapter Summary

This chapter has provided an overview of the entire study. It introduced the background and significance of the study, clarified the research problem, highlighting the research questions and objectives, along with the potential contributions of this study. Key contextual issues such as food production in China, food security, agricultural challenges, and the role of agricultural insurance were also discussed. By critically examining the relevant literature, this chapter has laid a solid foundation for the subsequent analysis. The

remainder of the thesis builds upon this foundation to investigate the impact of agricultural insurance on agricultural total factor productivity in China through both theoretical exploration and empirical evaluation.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive review of the existing literature related to agricultural insurance, agricultural productivity, and the institutional factors that affect their relationship. This review aims to identify the gaps in the study, integrate theoretical and empirical study results, and lay the foundation for the construction of the research framework and hypotheses of this study.

The review is divided into several key sections. Firstly, it explores the concepts and roles of agricultural productivity and agricultural insurance. Secondly, it reviews the related research on moral hazard and country governance. Thirdly, it examines the relevant theories of agricultural total factor productivity. Finally, it talks about the research on how agricultural insurance affects agricultural total factor production as well as the factors that influence it.

2.2 Concept of Agricultural Productivity

Agricultural productivity is a fundamental concept in agricultural economics, referring to the efficiency with which agricultural inputs are transformed into outputs. It reflects the overall performance of the agricultural production process and is widely used to assess agricultural development levels, food production capacity, and long-term economic sustainability (Fuglie, 2012; Hayami & Ruttan, 1985). Owing to biological

production cycles, climatic uncertainty, and market volatility, agricultural productivity encompasses broader dimensions than productivity in non-agricultural sectors.

Early studies conceptualized agricultural productivity primarily through partial productivity indicators, such as land productivity (output per unit of land) and labor productivity (output per worker). While these indicators are intuitive, they capture only the contribution of a single input and fail to reflect interactions and substitution among multiple production factors, potentially leading to biased interpretations of productivity performance (Hayami & Ruttan, 1985; Antle & Capalbo, 1988).

To address these limitations, scholars increasingly adopted the concept of total factor productivity (TFP) as a comprehensive measure of agricultural productivity. Based on growth theory, Solow (1957) defines TFP as the component of output growth that cannot be explained by the accumulation of conventional inputs, instead reflecting technological progress and efficiency improvement. In agriculture, TFP is widely understood as capturing advances in production technology, improvements in managerial efficiency, and better allocation of scarce resources under conditions of uncertainty (Coelli et al., 2005; Fuglie, 2012).

Agricultural productivity theory further emphasizes the sector's structural and institutional characteristics. Hayami and Ruttan (1985) propose the theory of induced technological change, arguing that agricultural productivity growth is shaped by relative factor scarcities and institutional arrangements. This perspective highlights that agricultural productivity is not solely a technical concept but also an economic and institutional outcome influenced by policy environments and factor endowments.

Subsequent literature views agricultural productivity as a dynamic and multidimensional concept, reflecting continuous changes in technology, efficiency, and production structure over time (Antle & Capalbo, 1988; Coelli et al., 2005). Accordingly, agricultural TFP growth is regarded as a key indicator of sustainable agricultural development, as it captures long-term improvements in production performance beyond simple input expansion.

Overall, the evolution of the agricultural productivity concept — from partial productivity measures to a comprehensive TFP-based framework — has provided a solid theoretical foundation for empirical analyses of agricultural development. This conceptual understanding supports the widespread use of agricultural TFP as a core indicator in studies examining productivity dynamics and policy impacts in agriculture.

2.3 The Concept and Role of Agricultural Insurance

While Section 1.7 and 1.8 provides some context on agricultural insurance, this section goes further by illustrating its concepts and implications in-depth, starting by highlighting concepts, followed by functions, and finally the roles of agricultural insurance.

2.3.1 The Concept of Agricultural Insurance

Agricultural insurance is defined in two ways: broadly—as insurance including farmers, agriculture, and rural areas, and narrowly, as insurance involving just agricultural producing activities and farmers' income (Huang, 2011); and in a narrow sense—an institutional arrangement whereby agricultural producers transfer the losses of agricultural property caused by disasters and accidents in the process of agricultural production to

insurers by paying small insurance premiums (Zhang et al., 2010). It is a general term for various types of insurance in which agricultural producers engage in crops, trees, livestock, poultry and other raising animals in the process of planting and breeding production (Kramer et al., 2007). Food security, agricultural modernization, farmer income assurance, and rural rejuvenation are all strongly influenced by agricultural insurance (You, 2023).

Agricultural insurance, as defined in the Regulations on Agricultural Insurance implemented in China in 2013, refers to insurance activities that provide compensation for property losses suffered by the insured due to natural disasters, accidents, epidemics, diseases, and other covered events occurring during the production processes of crop farming, forestry, animal husbandry, and fisheries. Under such contracts, insurers assume the liability for compensation in exchange for premium payments. The concept and scope of the agricultural economy, meanwhile, continue to evolve in response to shifts in human society. As economic structures, technological capabilities, and environmental conditions change, so too does the understanding of agricultural production, risk management, and the broader role of agriculture within national and global economies.

Accordingly, a concept that is always evolving and has varying meanings and applications in various eras and nations is agricultural insurance aimed at the agricultural sector (Chai, 2014).Implementing agricultural insurance can improve the ability to protect farmers' financial interests, lessen the detrimental effects of agricultural disasters on agricultural economic growth, and increase the stability of agricultural economic growth across different regions (Kulawik, 2018). According to Ahmed (2015), the Spanish government's policy agricultural insurance measures have produced impressive results,

showing that adding new insurance types can significantly increase farmers' insurance income in addition to successfully meeting their insurance needs.

2.3.2 The Function of Agricultural Insurance

From the government's point of view, agricultural insurance can avoid and transfer agricultural risks, providing risk protection for agricultural production and rural economic development (Kramer et al, 2022). Agricultural insurance, in the eyes of farmers, might lessen the level of risk they face, promote the development of rural credit and finance (Feng et al, 2007), and stabilize and increase the income of farmers. Agricultural insurance is one of the key contents of the national agricultural disaster reduction and disaster prevention management mechanism, which can provide indispensable strong support and reliable protection for the in-depth implementation of the rural revitalization strategy (Xie, 2022).

From the perspective of insurance institutions, agricultural insurance is a quasi-public good that can create a successful insurance market under government financial subsidies, promoting the exploration of successful agricultural insurance operation methods by insurance institutions, fostering the healthy and sustainable growth of insurance institutions, and ultimately creating a stable and sustainable agricultural insurance supply (Li, 2019). Farmers that experience losses may receive financial compensation through enhancing the agricultural insurance operational mechanism and the big catastrophe risk dispersion mechanism (Zeng, 2020). Regardless of perspective, risk protection remains the primary function of agricultural insurance. By playing the function of risk dispersion, agricultural insurance can stabilize the output expectation of agricultural

producers, and then encourage them to choose more efficient but potentially more risky production technology and production objects, and improve their production enthusiasm (Vyas et al., 2021). Second, agricultural insurance has the function of loss compensation. As a financing mechanism for financial loss after the event, it helps farmers quickly recover production by providing insurance compensation in time (Timu & Kramer, 2023).

2.3.3 The Role of Agricultural Insurance

Agricultural insurance plays a vital role in promoting efficient and resilient agricultural development. First, it contributes to the optimal allocation of agricultural resources and supports sustainable agricultural growth. As noted by Zou and Mishra (2022), agricultural insurance enhances resource efficiency by mitigating risks and stabilizing operations across the four key stages of agricultural reproduction—production, distribution, exchange, and consumption—thereby improving the overall allocation of agricultural inputs (Zheng, 2023).

Second, agricultural insurance helps alleviate the fiscal burden on governments in the aftermath of natural disasters. Policy-based agricultural insurance premiums are typically financed jointly by the government and farmers, with the state providing subsidies and farmers covering the remaining portion (Zhao & Lv, 2025). This risk-sharing mechanism allows for the pooling of social funds, reducing the strain on public disaster relief expenditures when major calamities occur (An, 2020).

Third, agricultural insurance contributes to safeguarding agricultural production and stabilizing grain output. Given the high uncertainty and vulnerability inherent in agricultural activities, effective risk management is essential (Jensen et al., 2024).

Agricultural insurance not only helps mitigate potential losses before disasters occur but also provides compensation afterward, facilitating timely recovery and ensuring continuity in agricultural production (Yin, 2023).

Fourth, agricultural insurance helps reduce farmers' livelihood concerns and contributes to broader social stability. By mitigating the adverse impacts of agricultural risks, insurance empowers farmers to maintain and even increase their investments in production, thus supporting income stability and expanded reproduction (Rastgoo et al., 2024). As a result, it plays a crucial role in sustaining rural livelihoods and promoting long-term social cohesion (Wang, 2021).

2.4 Moral Hazard

Moral hazard is a central concept in economics and insurance theory, arising from situations characterized by information asymmetry between contracting parties. It refers to behavioral changes that occur after a contract is signed, whereby one party engages in actions that increase risk exposure or reduce effort because the associated costs are partially borne by another party (Arrow, 1963; Pauly, 1968). Unlike adverse selection, which operates ex ante, moral hazard is an ex post phenomenon that affects outcomes through altered incentives and unobservable behavior.

The theoretical foundations of moral hazard are rooted in principal–agent theory, where the principal cannot fully observe or verify the agent's actions. Arrow (1963) first articulated the welfare implications of moral hazard in insurance markets, noting that insurance coverage can weaken incentives for risk prevention. Pauly (1968) further formalized the concept by emphasizing that moral hazard arises not from irrational

behavior but from rational responses to altered incentive structures under insurance protection.

Subsequent theoretical work expanded the moral hazard framework by highlighting the trade-off between risk sharing and incentive provision. Holmström (1979) demonstrates that optimal contracts must balance insurance against income risk with incentives for effort, implying that complete insurance is rarely optimal when effort is unobservable. This insight has become a cornerstone of modern contract theory and underpins much of the empirical research on insurance and productivity.

From a productivity perspective, moral hazard affects agricultural outcomes by distorting input allocation and weakening effort incentives, thereby reducing technical efficiency and total factor productivity. Goodwin and Smith (2013) argue that while insurance may stabilize income, excessive coverage or subsidies can erode production discipline and lead to efficiency losses. Empirical evidence from China and other developing countries suggests that high subsidy ratios may exacerbate moral hazard, limiting productivity gains and increasing fiscal pressure on insurance systems (Xiu & Lyu, 2020; Zhao et al., 2022).

However, the literature also highlights that moral hazard is not inevitable. Its magnitude depends on contract design, governance quality, and complementary institutions. Mechanisms such as deductibles, experience rating, and effective monitoring can mitigate moral hazard and allow insurance to function as a productivity-enhancing risk management tool (Holmström, 1979; Goodwin & Smith, 2013).

In summary, the moral hazard literature demonstrates that insurance-induced behavioral responses play a critical role in shaping production outcomes under risk. In the context of agricultural insurance, moral hazard represents a key behavioral mechanism

through which insurance may weaken or condition its impact on productivity. Ignoring moral hazard may lead to overestimation of the productivity benefits of insurance and contribute to the mixed empirical findings in existing studies. Therefore, incorporating moral hazard into empirical analyses is essential for understanding the true relationship between agricultural insurance and agricultural productivity.

2.5 Country Governance and Agricultural Productivity

More and more individuals are realizing the value of good governance to the social and economic advancement of a country as the economy and society improve. According to Kaufmann et al. (2005), governance can be thought of as the customs and institutions that a nation uses to wield its power. The researcher thinks that the development of agriculture depends much on the rule of law. People might choose to steal food in an easier way rather than work for it, if there is no legislation and no authority strictly enforces the law. As a result, nobody will want to work, and eventually, hunger may affect the entire world.

According to Fan et al. (2004), the ability of the government to create and carry out sound policies as well as offer public goods and services is what is meant by government effectiveness. The growth of agriculture is inextricably linked to the supply of public services and amenities including power plants, highways, and communication infrastructure. The ability of the government to deliver high-quality services and public goods is crucial for the growth of the rural economy. Government instability, according to Binswanger and Deininger (1997), would have an effect on public goods investment. Politically stable country will favor investing in public goods that can spur long-term

economic and social development. The leader is less likely to undertake long-term investments if the nation is politically unstable and the people do not trust them. As a result, the leader's tenure in office will be significantly reduced.

Governance, voice and accountability, regulatory quality, anti-corruption, political stability, government effectiveness, and the rule of law are the six governance areas identified by the World Bank. These six metrics have developed into useful instruments for assessing a country's governance. According to Kaufmann et al. (2024), these six indicators are interconnected, and the efficacy of one indicator is reliant on the efficacy of other indicators. For instance, the government's pertinent policies must be put into practice. The political environment needs to be stable at the moment, and the populace must have complete faith in the government. If corruption is rampant at this period and the populace begins to distrust the government, it will cause instability within the government and make it challenging to put the government's policies into action.

Research by Monchi et al. (2008) revealed that agricultural output increased in direct proportion to a country's degree of governance. By encouraging the accumulation of agricultural capital, improved governance levels not only directly increase agricultural productivity but also indirectly increase labor productivity. According to Nizamettin et al. (2012), while education is inversely connected with agriculture, the quality of oversight in country governance positively affects agricultural development. The greater the amount of education, the greater the percentage of people who avoid agricultural work. According to Akshi et al. (2020), country government encourages the introduction of development plans and corresponding policies. According to Wang et al. (2023), the country can successfully encourage the growth of agricultural productivity by providing financial aid to the sector.

According to the aforementioned research, a country with political stability, well-contained corruption, and an effective government is better able to improve public goods and services and adopt top-notch policies to support agricultural development. National government is crucial for the growth of agriculture (Barbosa, 2024).

2.6 Control variables

i. The Agricultural Structure

Existing studies demonstrate that agricultural structure significantly shapes regional differences in agricultural productivity by affecting factor allocation efficiency, technological adoption, and industrial composition (Hu et al., 2021). Accordingly, empirical analyses commonly include agricultural structure—such as crop composition, the share of livestock production, or structural rationalization indices—as key control variables to eliminate bias caused by structural heterogeneity across regions (Zhang & Yang, 2024). Prior research also confirms that structural adjustment is closely related to changes in agricultural TFP, meaning that omitting this variable may lead to over- or under-estimation of the impact of policy variables such as agricultural insurance or digitalization (Li & Wang, 2024).

ii. Disaster Impact

Disaster impact constitute an important external shock that directly affects agricultural output, production decisions, and productivity. Therefore, disaster impact is widely included as a control variable in empirical studies examining agricultural total factor productivity (TFP), agricultural insurance, climate risk, and rural development.

Failure to control for disaster shocks may lead to omitted variable bias, as disaster events significantly influence short- and long-term production outcomes (Klomp & Valckx, 2014).

Because disaster frequency and intensity are spatially heterogeneous, controlling for disaster impact helps isolate the true causal effect of policy variables such as agricultural insurance, rural credit, or digital adoption. For example, areas with higher disaster exposure may simultaneously have stronger policy interventions, which would bias estimates if disaster risk is omitted (Eskander & Barbier, 2016). Consequently, empirical models commonly incorporate disaster indicators—either contemporaneous or lagged—to account for both immediate losses and medium-term recovery effects (Ren et al., 2024).

iii. Rural Human Capital

The literature consistently identifies rural human capital as a key determinant of agricultural performance, making it an essential control variable in empirical analyses of agricultural productivity, technology adoption, and policy impacts. Elevated levels of human capital—commonly assessed via years of education, literacy, or skill composition—augment farmers' ability to obtain, analyze, and utilize information, thus facilitating the adoption of contemporary technologies and optimizing the allocation of production inputs (Hu, 2023).

A variety of indicators are used to measure rural human capital, including average schooling years, the distribution of educational attainment, and weighted indices that reflect heterogeneous productivity effects across different education levels (Zhou & Li, 2023). Some studies also incorporate broader proxies such as health status, participation in training, or agricultural experience to capture additional dimensions of human capital

where data are available (Baiyegunhi et al., 2010). Employing these measures allows researchers to better isolate the contribution of education-related capabilities from the effects of policy variables such as agricultural insurance, subsidies, or digital technologies on total factor productivity (TFP).

Empirical evidence shows that higher rural human capital is positively associated with technology adoption, production efficiency, and agricultural TFP. Failure to include human-capital indicators can bias estimated policy effects due to unobserved differences in farmers' skills and learning abilities (Foster & Rosenzweig, 2010). Consequently, rigorous studies routinely incorporate human capital controls and conduct robustness checks with alternative human capital measures to ensure the reliability of empirical findings.

iv. Urbanization Rate

Urbanization is widely recognized as a structural force shaping regional economic development, resource allocation, and technological diffusion. Consequently, the urbanization rate—typically measured as the proportion of the urban population in the total population — is commonly included as a control variable in empirical analyses of agricultural productivity, technology adoption, and rural development. Accounting for urbanization helps capture underlying heterogeneity in socioeconomic development across regions and avoids biased estimates of the effects of policy variables (Jin, 2022).

From a theoretical perspective, rising urbanization promotes improvements in infrastructure, transportation networks, public services, and information flows, all of which strengthen rural–urban linkages. These improvements reduce transaction costs and expand market access, thereby facilitating the dissemination of modern agricultural technologies

and knowledge (Liu & Zhang, 2021). Urbanization also enhances labor mobility, enabling surplus rural labor to shift to non-agricultural sectors and contributing to a more efficient reallocation of production resources within agriculture (Christiaensen & Todo, 2014). Such structural changes support agricultural modernization and efficiency improvements. Empirical evidence confirms these mechanisms: Zhou et al. (2019) show that urbanization in China generates positive spillover effects on agricultural productivity through resource integration and technological diffusion.

Overall, the literature demonstrates that urbanization is an important determinant of productivity dynamics through its effects on market expansion, technology diffusion, resource mobility, and rural transformation. Including the urbanization rate as a control variable strengthens empirical models and ensures more robust and unbiased estimates of agricultural performance (Zhang & Zhou, 2020).

v. The Power Level

Power availability is an important component of rural infrastructure and is therefore widely included as a control variable in studies of agricultural productivity. Rural electricity consumption reflects the capacity of local production systems to support energy-intensive agricultural activities, including irrigation, mechanization, storage, and processing. Higher electricity access reduces labor constraints, enhances production efficiency, and facilitates the adoption of modern technologies (Zhou, 2022).

Empirical evidence confirms the productive role of electricity. Nwachukwu and Egwu (2017) show that electricity consumption significantly increases agricultural output in rural Nigeria by enabling mechanization and improving operational efficiency. Similarly, Adams and Klobodu (2019) find that energy infrastructure — both renewable and non-

renewable — positively affects long-term agricultural total factor productivity in sub-Saharan Africa. These findings suggest that electricity availability is a critical determinant of agricultural modernization and productivity performance.

Accordingly, including power level as a control variable helps account for heterogeneity in infrastructural development across regions and ensures more accurate estimation of policy effects on agricultural productivity.

vi. Per Capita Disposable Income of Rural Residents

Per capita disposable income of rural residents is commonly included as a control variable because it captures households' economic capacity to invest in agricultural inputs, adopt modern technologies, and respond to policy incentives. Higher income levels relax liquidity constraints, enable greater investment in machinery, improved seeds, fertilizers, and risk-management tools, and enhance households' resilience to shocks (Dercon & Christiaensen, 2011). Income growth also contributes to human capital improvement — such as better nutrition, education, and health—which in turn raises labor productivity and facilitates technology adoption (Fan et al., 2013).

Empirical studies confirm the importance of rural income for agricultural performance. Reardon et al. (2019) show that higher rural income supports modernization and input upgrading in developing regions, while Foster and Rosenzweig (2010) find that wealthier households are more likely to adopt productivity-enhancing technologies due to reduced risk aversion and improved financial flexibility. In China, Liu and Wang (2020) report that rising rural disposable income accelerates mechanization and improves agricultural efficiency.

Therefore, controlling for rural per capita income is essential for isolating the effects of agricultural policies and avoiding omitted-variable bias when analyzing productivity outcomes.

2.7 Related Theories

In this section, the related theories applicable for this study are explored, such as agricultural risk management theory, agricultural productivity theory, information asymmetry.

2.7.1 Agricultural Risk Management Theory

Natural disasters, external shocks, and changes in the market for agricultural products are just a few of the risks that will unavoidably affect the entire agricultural production and operation process, from inputs to output to sales (Moschini et al., 2001). Agriculture is a fragile and high-risk industry. It is essential to aggressively investigate suitable procedures and tactics to prevent and address various agricultural hazards through effective management of agricultural risks if China is to raise its agricultural TFP and promote the high-quality development of agriculture (Yang, 2023).

It is generally believed that agricultural risk management refers to the process in which risk management entities actively identify risks, measure risks and analyze risks, and select appropriate risk management tools to disperse and transfer various agricultural risks (Tack & Yu, 2021). Considering the choice of agricultural risk management tools, agricultural insurance has developed into one of the crucial instruments for agricultural risk management because it can efficiently disperse and transfer related risks, lower farmers'

risk expectations, and provide strong guarantee for the development of the agricultural industry (Zheng, 2023).

Specifically, the main ways in which agricultural insurance plays its role as a risk management tool include: pre-event risk prevention and post-event risk compensation (Li, 2023). The former indicates that insurance firms will utilize all of their expertise in loss mitigation and disaster prevention, and will direct insured farmers to take the necessary proactive actions in advance to minimize the likelihood of agricultural risks (Bencová & Boháčiková, 2021); The latter is that after the farmers really suffer losses, the insurance company pays compensation to the insured farmers in a timely manner according to the agreement, reducing the impact of risks on farmers and agricultural production, reducing the volatility of farmers' income, and enabling them to resume agricultural production as soon as possible, thereby ensuring the sustainability of agricultural production (Qiao, 2021).

In conclusion, agricultural risk management theory underpins this study by explaining how agricultural insurance influences agricultural total factor productivity through risk reduction and behavioral responses. When production and market risks are unmanaged, farmers tend to adopt conservative strategies, reduce investment in modern inputs, and allocate production factors inefficiently, thereby constraining productivity growth (Moschini & Hennessy, 2001; Tack & Yu, 2021). Agricultural insurance functions as a risk-transfer mechanism that stabilizes expected income and reduces uncertainty, which encourages productive investment, facilitates the adoption of advanced technologies, and improves input allocation efficiency (Feng et al., 2021; Jin et al., 2022). These

behavioral and efficiency improvements enable farmers to operate closer to the production frontier, resulting in higher agricultural TFP (Coelli et al., 2005).

However, agricultural risk management theory also emphasizes that the productivity effect of insurance is conditional rather than automatic. When insurance coverage is insufficient, risk mitigation may be too weak to alter farmers' production decisions, yielding limited productivity gains. Conversely, excessively generous insurance coverage or subsidy intensity may weaken effort incentives and induce moral hazard, offsetting the productivity gains from risk reduction (Goodwin & Smith, 2013; Xiu & Lyu, 2020). Therefore, agricultural insurance affects agricultural TFP through a combination of risk management, efficiency enhancement, and incentive mechanisms.

2.7.2 Agricultural Productivity Theory

Agricultural production theory is an important foundational theory in agricultural economics, with its core being the revelation of the technical relationships between various input factors and output during the agricultural production process. Traditional agricultural production theory usually assumes that farmers, under the premise of rational decision-making, pursue the goal of output maximization or cost minimization at a specific technological level based on limited resource endowments (such as land, labor, and capital) (Chavas, 2008).

On this basis, the Total Factor Productivity theory further develops the connotation of traditional production theory. The concept of TFP originates from modern growth theory and is used to measure the efficiency improvements in output growth brought about by non-material inputs such as technological progress, institutional

optimization, and management efficiency enhancements, after excluding the impact of increased quantities of various factor inputs (Alston & Pardey, 2014). Compared to merely examining the marginal output of a single factor, TFP theory places greater emphasis on the synergy and combination efficiency among multiple factors. It posits that the improvement in agricultural production efficiency relies not only on the quantity of resource inputs but also on the scientific allocation of resources and advancements in technological levels (Zhang, 2022).

In the agricultural field, the theory of total factor productivity can be used to assess the output level in the agricultural production process to clearly identify the paths for improving agricultural productivity. It takes into account various production factors in agricultural production, including but not limited to the cultivated area, labor force, funds, and production technology, and through comprehensive consideration of the combination and utilization effect of these production factors, achieves a more comprehensive and integrated assessment of the output level of agricultural production (Dhehibi et al., 2018) . Total factor productivity represents the output level of an industry, and its core idea is to subtract the growth of production factors from the growth of output, and calculate the comprehensive index by comparing the changes in output and the input of each production factor (Zong, 2024).

Therefore, changes in total factor productivity can lead to changes in comprehensive productivity. If the index increases, it indicates that the same productive input can achieve more output. In agricultural production, the theory of total factor productivity provides an important research theoretical framework. By evaluating the input and potential of different agricultural production resources, it can promote technological

progress and improvement of management levels through improving agricultural technology, optimizing resource allocation, etc. By continuously increasing the total factor productivity of agriculture, the goal of gradually improving agricultural production efficiency can be achieved (Zhu, 2024).

Applying this theory to agricultural production can help agricultural producers and operators recognize the potential directions for improving production efficiency, thereby formulating corresponding policies and measures to enhance production efficiency. On the other hand, by effectively utilizing production factors and improving comprehensive production efficiency, the production sector can also achieve higher output levels and achieve a low-consumption, environmentally friendly production mode (Sun, 2024). In summary, the theory of total factor productivity provides a comprehensive assessment and optimization of production efficiency for agricultural production, and is of great significance for the high-quality development of agriculture (Melfou et al., 2007).

In the realm of agricultural development, agricultural TFP has gained popularity as a key indicator of high-quality agricultural development. The primary composition framework and influencing elements of agricultural TFP have been elucidated by the application of the theory of total factor productivity. Thus, using the aforementioned theory of total factor productivity, this research examines the transmission mechanism of the effect of agricultural insurance on agricultural TFP.

2.7.3 Information Asymmetry

Information asymmetry is a fundamental concept in economics, referring to situations in which parties involved in an economic transaction possess unequal information regarding relevant characteristics, actions, or outcomes. When one party has

superior or more accurate information than the other, market outcomes may deviate from efficiency, giving rise to systematic distortions such as adverse selection[1] and moral hazard (Akerlof, 1970; Stiglitz, 1987). Information asymmetry is particularly prevalent in insurance markets, where risk types and effort levels are often privately observed by insured agents but imperfectly observable by insurers.

The seminal work of Akerlof (1970) introduced the concept of information asymmetry through the "market for lemons[2]," demonstrating how quality uncertainty can drive high-quality participants out of the market and lead to market failure. Building on this framework, Rothschild and Stiglitz (1976) formalized adverse selection in insurance markets, showing that asymmetric information regarding risk types can result in market segmentation or even the absence of equilibrium. These studies establish that information asymmetry fundamentally alters market structure and pricing mechanisms.

In contrast to adverse selection, which occurs ex ante, moral hazard arises ex post and reflects unobservable actions taken after a contract is signed. Arrow (1963) and Pauly (1968) highlight that insurance coverage may weaken incentives for risk prevention and effort when insured agents do not bear the full consequences of their actions. Together, adverse selection and moral hazard constitute the two primary channels through which information asymmetry affects insurance efficiency.

Information asymmetry is particularly acute in agricultural insurance markets due to the spatial dispersion of farms, the biological nature of production, and the stochastic

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[1] Reverse selection refers to a phenomenon where, due to information asymmetry, high-risk farmers (such as those more prone to natural disasters and pests and diseases) are more likely to purchase agricultural insurance than low-risk farmers. This leads to an increase in the insurance payout rate and a rise in premiums, which in turn forces low-risk farmers to withdraw from the insurance market, ultimately disrupting the balance of the insurance market.

[2] The lemon market (also known as the inferior product market) refers to a phenomenon where, due to information asymmetry, low-quality products (inferior goods or lemons) gradually drive out high-quality products, resulting in market contraction or even failure.

influence of weather and pests. Insurers often lack timely and accurate information about farmers' production conditions, input choices, and risk management efforts, while farmers typically possess private information about land quality, local climate, and managerial ability (Just et al., 1999). This asymmetry complicates risk assessment and contract enforcement.

Empirical studies indicate that information asymmetry leads to significant adverse selection in agricultural insurance, as high-risk farmers are more likely to purchase coverage, while low-risk farmers may withdraw due to unfavorable premium–risk trade-offs (Ankrah et al., 2021). Over time, this dynamic increases loss ratios and threatens the sustainability of insurance programs. Moreover, moral hazard behavior—such as reduced preventive effort or strategic loss reporting—has been widely documented in agricultural contexts, further undermining insurance effectiveness (Horowitz & Lichtenberg, 1993; Smith & Goodwin, 1996).

The literature increasingly recognizes that the severity of information asymmetry and its economic consequences depend on institutional and governance conditions. Strong regulatory frameworks, transparent contract design, and effective monitoring mechanisms can mitigate information asymmetry by reducing opportunistic behavior and improving incentive alignment (Stiglitz, 1987). Conversely, weak governance exacerbates information problems, leading to higher transaction costs and inefficient outcomes.

In agricultural insurance systems that rely heavily on public subsidies, information asymmetry may be amplified if monitoring and accountability mechanisms are insufficient. Several studies suggest that poor transparency in claim assessment and limited insurance literacy among farmers can erode trust and reduce participation, further weakening the insurance–productivity linkage (Dougherty et al., 2021). These findings

highlight that information asymmetry is not only a market failure but also an institutional challenge.

From a productivity perspective, information asymmetry affects agricultural outcomes by distorting farmers' production incentives and input allocation decisions. Adverse selection and moral hazard reduce the effectiveness of insurance as a risk management tool, potentially offsetting its productivity-enhancing benefits. As a result, the impact of agricultural insurance on agricultural total factor productivity is likely to be heterogeneous and conditional on the degree of information asymmetry and institutional quality.

Overall, the information asymmetry literature provides a critical theoretical foundation for understanding why agricultural insurance may generate mixed productivity effects and why moral hazard and governance quality should be explicitly incorporated into empirical analyses of insurance–productivity relationships.

2.8 Influencing Factors of Agricultural Total Factor Productivity

Numerous research findings have been made about the variables that affect agricultural TFP. Combing the relevant literature is conducive to enhancing our understanding of agricultural TFP and laying a foundation for subsequent research. Following a summary of the existing research, it is concluded that scholars primarily investigate the institutional change, environmental factors and economic factors that influence agricultural TFP.

Scholars have consistently confirmed that the reform of the land system has a positive impact on the increase of agricultural total factor productivity in terms of

institutional change. For example, Lin (1992) found through research that after the implementation of the family co-production underwriting liability system in China, the "institutional dividend" was quickly released, which greatly promoted the improvement of China's total factor productivity at that time. According to Chari et al. (2020), the Rural Land Contract Law's implementation enhanced the land leasing activities of rural families, sped up land circulation, and transferred land to farmers who could produce higher yields, all of which had a beneficial effect on agricultural TFP.

In terms of natural factors, most scholars think that the natural environment constraint is the important reason to restrain the further growth of agricultural TFP in our country. For example, Ogundari et al. (2021) conducted a study on Africa, analyzing the impact of climate change on the growth of agricultural TFP in Africa. The study concluded that temperature has no significant impact, while rainfall significantly promotes growth. Chancellor et al. (2021) focused their empirical research on the TFP of non-irrigated agriculture in Australia, concluding that climate factors have a significant impact on agricultural TFP, which may affect the actual effects of technological progress. In general, the changes of agricultural land system and the improvement of economic conditions have significantly increased the agricultural TFP in China, while the constraints of natural environment have a negative impact on agricultural TFP.

The majority of academics focus on rural human capital first when discussing individual characteristics. It is yet unknown how rural human capital affects agricultural TFP. The majority of academics think that rural human capital may have a significant influence on the expansion of agricultural TFP. For example, according to Gao (2015) and Yang et al. (2019), rural human capital positively affects agricultural TFP through the

development of new agricultural technologies. Yu et al. (2020) believes that agricultural TFP and rural human capital promote each other, but the interaction is heterogeneous. Pietrzak and Balcerzak (2016) analyze the quality of human capital from a knowledge perspective and confirm that human capital is an important driver of agricultural TFP growth in the new European member States. However, some scholars hold different views.

Through empirical research, Zhou et al. (2018) discovered that the size of the cultivated area limits the effect of rural human capital on agricultural TFP. Rural human capital will only benefit agricultural TFP when agriculture is practiced on a broad scale. The influence of rural human capital on agricultural TFP is not as clear-cut, according to Yin (2020), because the promotion of urbanization and industrialization will lead farm laborers with higher education to transfer to the secondary and tertiary industries. According to Li et al. (2021) the loss of certain highly skilled rural workers will accompany the strengthening of rural human capital, which will ultimately result in a reduction in agricultural TFP. Rural human capital has a significant positive impact on the expansion of agricultural TFP as a result of the Internet's influence. A positive contribution to the promotion of agricultural TFP is made by the widespread use of rural Internet.

2.9 Effect of Agricultural Insurance on Total Factor Productivity

A growing body of literature has examined the impact of agricultural insurance on agricultural productivity, particularly total factor productivity (TFP). However, existing studies differ substantially in terms of empirical methodology, geographical focus, and time coverage, leading to mixed and sometimes contradictory conclusions. To clarify the evolution of this literature and identify remaining research gaps, this section provides a

structured synthesis of prior empirical studies based on three key dimensions: methodology, country or regional focus, and study period.

From a methodological perspective, existing studies mainly adopt panel regression models, efficiency and productivity measurement methods, and nonlinear models. Early studies primarily relied on panel regression frameworks to investigate how agricultural insurance affects production behavior and productivity-related outcomes. For example, Horowitz and Lichtenberg (1993) and Smith and Goodwin (1996) employ farm-level panel data and regression models in the United States to examine how crop insurance influences input use and production decisions, providing indirect evidence on productivity effects through moral hazard mechanisms. Complementing these micro-level analyses, Goodwin and Smith (2013) conduct a comprehensive policy evaluation of the U.S. crop insurance system and argue that heavily subsidized insurance may weaken production discipline and reduce efficiency, thereby offsetting potential productivity gains.

With the increasing availability of regional and national datasets, more recent studies have incorporated total factor productivity measures, often constructed using DEA-Malmquist indices or stochastic frontier analysis (SFA). Jin et al. (2022) use a DEA-Malmquist approach to measure agricultural TFP across Chinese provinces and subsequently examine the effect of agricultural insurance on productivity growth using panel regressions. Similarly, Feng et al. (2021) analyze how crop insurance affects production decisions and efficiency by linking insurance participation to technology adoption and investment behavior, highlighting an indirect productivity-enhancing channel through risk mitigation.

In addition, a smaller but growing strand of literature employs nonlinear and threshold models to capture heterogeneous effects. Xiu and Lyu (2020) apply a panel threshold model to investigate how subsidy intensity influences insurance efficiency and moral hazard in China, demonstrating that the productivity effects of agricultural insurance vary across different stages of insurance development. Their findings suggest that excessive subsidies may exacerbate moral hazard and weaken efficiency, underscoring the importance of accounting for nonlinear relationships.

In terms of geographical focus, the literature can be broadly divided into studies on developed economies and those on developing or transition economies. Studies focusing on developed countries, particularly the United States, typically rely on farm-level or county-level data to examine behavioral responses to agricultural insurance. These studies emphasize moral hazard, input substitution, and efficiency loss as key channels through which insurance affects productivity (Horowitz & Lichtenberg, 1993; Smith & Goodwin, 1996; Goodwin & Smith, 2013).

In contrast, research on developing and transition economies—especially China—has increasingly focused on macro- or regional-level productivity effects. Using provincial panel data, studies such as Feng et al. (2021), Xiu and Lyu (2020), and Jin et al. (2022) examine how insurance development interacts with investment, technology adoption, and institutional factors to influence agricultural TFP. Beyond China, Ankrah et al. (2021) analyze agricultural insurance participation in developing economies and provide evidence of adverse selection, suggesting that information asymmetry may limit the effectiveness of insurance programs and indirectly constrain productivity improvements. Similarly, Ceballos et al. (2017), using experimental and survey data from developing countries,

show that insurance programs may fail to generate sustained productivity gains when contract design and behavioral responses are not adequately addressed.

Regarding time coverage, earlier studies often rely on relatively short datasets due to data constraints, typically covering fewer than ten years. For instance, early U.S.-based studies analyze data from the late 1980s to early 1990s, limiting their ability to capture long-term productivity dynamics and structural change. More recent studies benefit from longer panel datasets spanning over a decade. For example, Xiu and Lyu (2020) examine Chinese agricultural insurance data from 2007 to 2016, while Jin et al. (2022) extend the analysis to more recent years. Longer time coverage enables researchers to explore dynamic effects, structural adjustments, and nonlinear relationships between agricultural insurance and productivity.

Overall, the existing literature provides valuable insights into the relationship between agricultural insurance and agricultural productivity. However, substantial heterogeneity in methodology, geographical focus, and time coverage contributes to divergent findings. Many studies focus either on micro-level behavioral responses or on average macro-level effects, while relatively few integrate productivity measurement, institutional conditions, and behavioral mechanisms within a unified analytical framework. Moreover, existing research often assumes linear relationships and pays limited attention to how governance quality and moral hazard jointly condition the productivity effects of agricultural insurance. Addressing these gaps, the present study employs a long provincial panel dataset for China and explicitly examines the impact of agricultural insurance on agricultural TFP while incorporating governance quality, moral hazard, and threshold

effects. By doing so, this study provides a more comprehensive and policy-relevant understanding of how agricultural insurance influences agricultural productivity.

Table 2.1: Empirical Studies on the Effect of Agricultural Insurance on Agricultural Productivity

Author(s)	Methodology	Data Level	Country / Region	Time Period	Main Focus / Key Findings
Horowitz & Lichtenberg (1993)	Panel regression	Farm-level	United States	1986–1990	Insurance affects input use; evidence of moral hazard
Smith & Goodwin (1996)	Panel regression	Farm-level	United States	1988–1992	Insurance alters chemical input decisions
Goodwin & Smith (2013)	Policy evaluation	National / sectoral	United States	Historic al	Subsidized insurance may weaken production incentives
Feng et al. (2021)	Panel regression	Provincial-level	China	2007–2016	Insurance promotes investment and technology adoption
Xiu & Lyu (2020)	Panel threshold model	Provincial-level	China	2007–2016	High subsidies exacerbate moral hazard
Jin et al. (2022)	DEA-Malmquist + regression	Provincial-level	China	2007–2018	Insurance improves agricultural TFP
Ankrah et al. (2021)	Panel regression	Household / regional	Developing countries	Varies	Evidence of adverse selection
Ceballos et al. (2017)	Experimental & survey	Farm-level	Developing countries	Cross-sectional	Insurance design limits productivity effects

2.10 Conceptual Framework and Hypothesis of Study

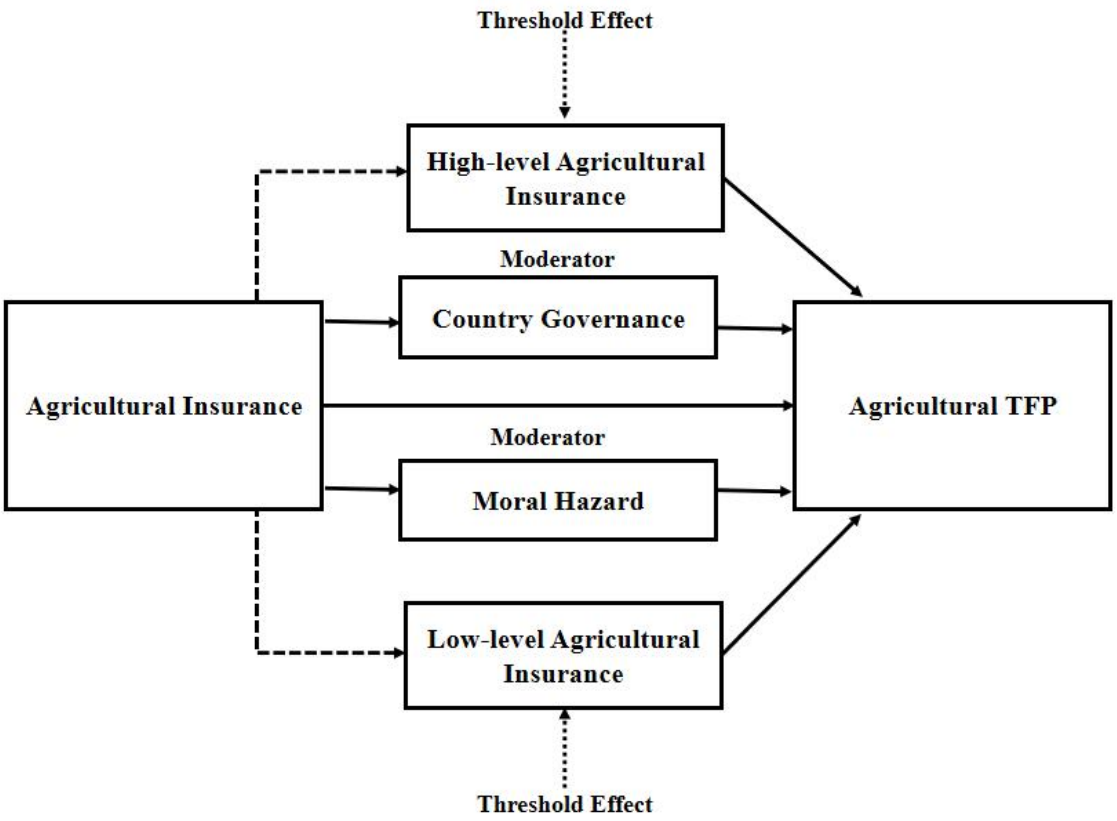

Figure 2.1: Conceptual Framework

The conceptual framework of this study is illustrated in Figure 2.1. Agricultural insurance, as an effective risk reduction strategy, mainly alters agricultural production and operation behaviors through its characteristics such as risk dispersion, income guarantee, and mortgage loans, thereby influencing the total factor productivity of agriculture. National governance and moral risks will have an impact on agricultural insurance and subsequently affect the total factor productivity of agriculture.

First, according to agricultural risk management theory, agricultural production is highly exposed to natural and market risks, which increase income volatility and discourage long-term investment in productivity-enhancing activities (Tack & Yu, 2021).

By transferring production risks from farmers to insurers, agricultural insurance reduces uncertainty and stabilizes farmers' income expectations. This risk-reducing function enables farmers to make more rational production decisions, optimize input allocation, and adopt advanced technologies, thereby improving agricultural total factor productivity.

From the perspective of agricultural productivity theory, productivity growth depends not only on factor accumulation but also on technological progress and efficiency improvement. Agricultural insurance facilitates access to credit through insurance-backed loans and collateral mechanisms, alleviating financing constraints and promoting capital deepening and mechanization in agriculture. These channels encourage large-scale operations and technological upgrading, which are essential drivers of TFP growth (Xia et al., 2024).

Moreover, expected utility theory suggests that risk-averse farmers tend to underinvest in high-return but risky technologies. Agricultural insurance mitigates downside risks, increases farmers' willingness to invest in modern inputs, and enhances production efficiency (Tang et al., 2022). Therefore, agricultural insurance is expected to exert a positive effect on agricultural total factor productivity.

Second, according to agricultural productivity theory, improvements in agricultural total factor productivity arise primarily from technological progress, efficiency gains, and the optimal allocation of production factors rather than from factor accumulation alone (Coelli et al., 2005). The effectiveness of policy instruments in promoting agricultural productivity depends on whether they facilitate technology adoption, enhance production efficiency, and reduce resource misallocation (Fuglie et al., 2020). In this context, agricultural insurance can promote productivity by reducing production risk

and encouraging farmers to invest in advanced technologies and modern inputs (Tang et al., 2022). However, the extent to which agricultural insurance translates risk protection into productivity gains is conditional on the institutional and governance environment in which it operates (North, 1990).

In regions with high governance quality, agricultural insurance is more likely to function as an effective productivity-enhancing mechanism. Strong governance improves policy implementation efficiency, ensures transparent allocation of insurance subsidies, and strengthens supervision over insurance contracts and claims, thereby reducing distortions in input use and discouraging opportunistic behavior (Kaufmann et al., 2011). These governance attributes allow agricultural insurance to effectively stabilize farmers production expectations, increase confidence in long-term investment, and facilitate the adoption of productivity-enhancing technologies and scale-efficient production practices, leading to greater improvements in agricultural TFP (Fan et al., 2011).

By contrast, in regions with weak governance, deficiencies in administrative capacity and regulatory enforcement may impede the productivity-enhancing channels of agricultural insurance. Poor supervision can distort farmers' production decisions and exacerbate inefficiencies in factor allocation, weakening incentives for technological adoption and efficient input use (Hao, 2023). Under such conditions, agricultural insurance may fail to improve production efficiency and may even crowd out productive investment. Consequently, the positive effect of agricultural insurance on agricultural TFP is likely to be attenuated or offset in low-governance regions. This perspective is consistent with empirical evidence indicating that governance quality conditions the productivity effects of agricultural policies (Espoir et al., 2024).

Therefore, from the standpoint of agricultural productivity theory, country governance does not merely influence agricultural output directly but plays a critical moderating role by shaping the extent to which agricultural insurance improves production efficiency and technological progress.

Thirdly, according to information asymmetry theory, insurance markets are prone to moral hazard because insured agents may alter their behavior after obtaining coverage (Arrow, 1963). In agricultural insurance, moral hazard manifests when insured farmers reduce preventive effort, lower input intensity, or engage in opportunistic production behavior, knowing that losses will be compensated.

While agricultural insurance can theoretically improve factor allocation and productivity, the presence of moral hazard may distort production incentives and reduce efficiency. Excessive reliance on insurance compensation may discourage technological innovation and careful input management, thereby weakening the positive impact of insurance on agricultural TFP (Hao, 2023). Thus, moral hazard is expected to act as a negative moderator, constraining the effectiveness of agricultural insurance in enhancing agricultural productivity.

Fourthly, although agricultural insurance is generally expected to promote agricultural total factor productivity, its impact may not be linear across different stages of insurance development. According to nonlinear economic theory and policy effectiveness theory, the marginal effects of policy instruments often vary once a key variable surpasses a critical level, leading to structural changes in economic outcomes (Crespo Cuaresma et al., 2014). In the context of agricultural insurance, differences in coverage depth, premium subsidy intensity, and participation rates may result in heterogeneous productivity effects across provinces (Tang et al., 2022).

At low levels of agricultural insurance development, limited coverage and insufficient risk pooling may constrain the effectiveness of insurance in stabilizing farmers' income and reducing production uncertainty. Under such conditions, insurance may function primarily as a compensatory mechanism rather than as a productivity-enhancing tool, yielding only marginal improvements in factor allocation efficiency (Cai et al., 2020).

As agricultural insurance development exceeds a certain threshold, broader coverage and more mature insurance markets enhance risk-sharing capacity and strengthen farmers' confidence in production and investment decisions. Once this threshold is crossed, agricultural insurance can more effectively alleviate financing constraints, facilitate large-scale production, promote technological adoption, and improve the efficiency of input use, thereby exerting a stronger positive impact on agricultural TFP (Xia et al., 2024).

However, at very high levels of insurance development, excessive reliance on insurance protection — particularly in the presence of generous subsidies and weak supervision—may intensify moral hazard and reduce production incentives. In such cases, the marginal productivity gains from agricultural insurance may diminish or even turn negative, implying the possibility of multiple thresholds or regime-dependent effects (Hao, 2023).

This nonlinear mechanism is consistent with risk management theory, information asymmetry theory, and institutional economics, which jointly suggest that the productivity effects of agricultural insurance depend on both its development stage and the institutional environment in which it operates (Moschini & Hennessy, 2001).

Based on the above analysis, this study proposes the following three hypotheses.

Hypothesis H1: Agricultural insurance positively contributes to agricultural total factor productivity growth in China.

Hypothesis H2: Country governance positively moderates the relationship between agricultural insurance and agricultural total factor productivity, such that the productivity-enhancing effect of agricultural insurance is stronger in regions with higher governance quality in China.

Hypothesis H3: Moral hazard negatively moderates the relationship between agricultural insurance and agricultural total factor productivity, such that higher levels of moral hazard weaken the productivity-enhancing effect of agricultural insurance in China.

Hypothesis H4: The development of agricultural insurance exhibits a threshold effect on agricultural total factor productivity in China, such that the impact of agricultural insurance on agricultural TFP varies across different insurance development regimes.

2.11 Summary of chapter

Based on a systematic review of relevant literature, it can be found that existing research has not yet taken country governance and moral hazard as moderating variables to systematically examine the impact of agricultural insurance on agricultural total factor productivity. At the same time, there is a lack of research that uses agricultural insurance as a threshold variable to analyze its nonlinear impact on agricultural total factor productivity. Based on this, this paper first constructs a fixed effect model and a GMM model,

introduces country governance and moral hazard as moderating variables, and examines the mechanism of the impact of agricultural insurance on agricultural total factor productivity. On this basis, a threshold model is further constructed to analyze the threshold effect and nonlinear characteristics of the impact of agricultural insurance on agricultural total factor productivity.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter constructs an empirical analysis model of agricultural insurance on agricultural total factor productivity in China provinces. The research design, variable selection, and statistical analysis are presented in Sections 3.2 and 3.3. A model for determining the total factor productivity of agriculture in different Chinese provinces is built in Section 3.4 using the DEA-Malmquist productivity index approach. To investigate the effect of agricultural insurance on agricultural total factor production in Chinese provinces, a baseline regression model is built in Section 3.5. A moderating model that considers moral hazard and country governance as moderating variables is developed in Section 3.6 to investigate the impact of agricultural insurance on agricultural total factor productivity in Chinese provinces. Lastly, a threshold model is built in Section 3.7 to investigate the threshold effect of agricultural insurance on China provinces' agricultural total factor production.

3.2 Research Design

Firstly, the research framework is based on the theory of agricultural risk management. This theory holds that agricultural production faces high levels of uncertain natural and market risks. Unmanaged risks will enhance farmers' risk-averse behavior, inhibit their adoption of productive inputs and new technologies, thereby reducing production efficiency (Moschini & Hennessy, 2001; Tack & Yu, 2021). Agricultural

insurance, as a institutional risk transfer tool, reduces production uncertainty and stabilizes farmers' expected income, alleviating risk constraints and thereby influencing farmers' investment decisions, technology adoption, and factor allocation efficiency, having a positive impact on agricultural TFP (Feng et al., 2021; Jin et al., 2022). In the research framework, this theoretical mechanism corresponds to the development level of agricultural insurance as the core explanatory variable, and is depicted through a two-way fixed effects model for its average impact on agricultural TFP.

Secondly, the research framework introduces the theory of agricultural productivity (total factor productivity theory). This theory emphasizes that agricultural production efficiency has significant dynamic evolution characteristics, manifested as technological accumulation, learning effects, and path dependence. The current period's agricultural TFP is not only influenced by current inputs and policy environments, but also constrained by historical productivity levels (Solow, 1957; Coelli et al., 2005). Based on this theory, the research framework further introduces lagging terms on the basis of the fixed effects model and adopts a dynamic panel GMM model to depict the dynamic adjustment process of agricultural TFP and effectively handle the endogeneity and reverse causality issues that may exist between agricultural insurance development and agricultural TFP (Arellano & Bond, 1991; Blundell & Bond, 1998).

Thirdly, the research framework is based on the theory of information asymmetry, revealing the problems of adverse selection and moral hazard commonly existing in the agricultural insurance market. Due to the difficulty for insurance companies to fully observe farmers' risk types and production efforts, agricultural insurance may induce incentive distortions while enhancing risk protection, thereby weakening production

efficiency (Arrow, 1963; Pauly, 1968; Rothschild & Stiglitz, 1976). As the coverage and subsidy intensity of agricultural insurance increase, the problem of moral hazard may further intensify, causing different impacts of agricultural insurance on agricultural TFP at different development stages (Goodwin & Smith, 2013; Xiu & Lyu, 2020). Based on this theoretical logic, the research framework introduces moral hazard and governance quality as key regulatory mechanisms and uses a threshold model to depict the nonlinear and phased characteristics of agricultural insurance's impact on agricultural TFP, thereby identifying the critical range where agricultural insurance transitions from "risk mitigation effect dominance" to "incentive constraint effect manifestation" (Hansen, 1999).

As shown in Figure 3.1, in conclusion， this study first employs quantitative research methods to examine the impact of agricultural insurance on agricultural total factor productivity (TFP). Existing studies indicate that agricultural insurance can promote agricultural production efficiency and TFP by mitigating production risks, stabilizing farmers' expectations, and improving the allocation of production factors (Wang, 2025). Building on this foundation, the study constructs fixed effects models and system GMM models to effectively control for unobserved individual heterogeneity and address potential endogeneity issues (Wooldridge, 2010). Furthermore, country governance and moral hazard are incorporated as moderating variables to systematically examine the mechanisms through which agricultural insurance affects agricultural TFP. Finally, this study constructs a threshold model to investigate the threshold effects and nonlinear characteristics of agricultural insurance on agricultural TFP, thereby revealing the stage-dependent and heterogeneous impacts of agricultural insurance development (Cui, 2025).

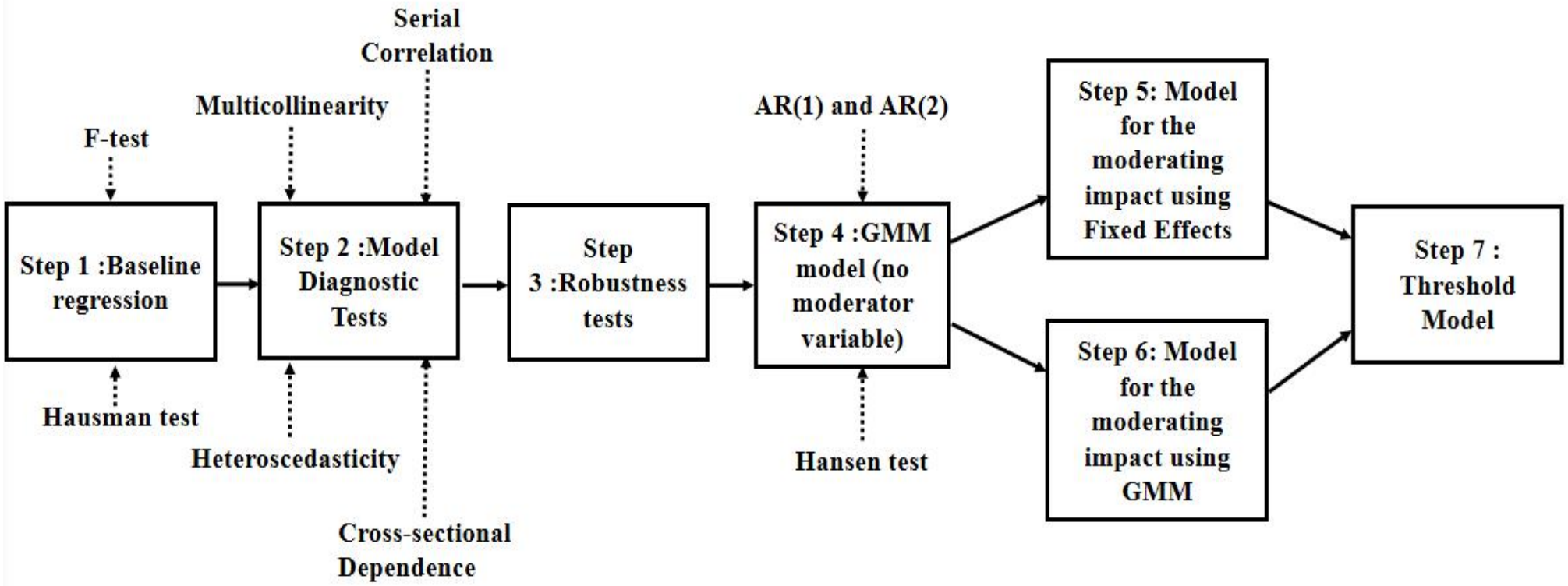

Figure 3.1: Flowchart of the model setup

3.2.1 Sample of Study

The data selected for the study are the panel data of 31 provinces in China between 2007 and 2023. The data of all 31 provinces in China are chosen to ensure full coverage and avoid the deviation in research results caused by the differences in geographical and economic conditions among selected provinces (Li et al., 2020). The data between 2007 and 2023 are selected because the pilot program of agricultural insurance was fully launched in 2007, and the central government of China provided special subsidies for agricultural insurance for the first time. Choosing 2007 as the starting point can capture the initial effects of policy intervention and avoid the problem of incoherent early data (Lin & Zhou, 2025).

The data in this study mainly involve three variables: first, the dependent variable which is agricultural total factor productivity, and proxy by DEA-Malmquist productivity index; Second, the independent variable which is agricultural insurance. Other independent variables, include the level of agricultural structure, disaster impact, rural human capital, urbanization rate, the power level and per capita disposal income of rural residents.

3.2.2 Data Sources

The data used in this thesis are obtained from China Statistical Yearbook (2008-2024), China Insurance Statistical Yearbook (2008-2024), China Rural Statistical Yearbook (2008-2024), China Population and Employment Statistical Yearbook (2008-2024), the World Bank's World Governance Indicators (WGI) database.

Among them, the variables used to calculate total factor productivity in agriculture—such as the number of primary industry practitioners, total sown area of crops,

total power of agricultural machinery, agricultural fertilizer application, and added value of the primary industry—are obtained from the China Statistical Yearbook (2008–2024).

The data of the independent variable agricultural insurance is derived from the China Insurance Statistical Yearbook (2008–2024). The other independent variables include indicators such as agricultural structure, disaster impact, urbanization rate, and agricultural power level, which are collected from the China Rural Statistical Yearbook (2008–2024). Additionally, data on rural human capital and per capita disposable income of rural residents are drawn from the China Population and Employment Statistical Yearbook (2008–2024).

The moderating variables—moral hazard and country governance quality—are obtained from the China Statistical Yearbook (2008–2024) and the World Bank's World Governance Indicators (WGI) database, respectively.

3.3 Variable Definitions and Descriptions

This study constructs a comprehensive variable system to examine the impact of agricultural insurance on agricultural total factor productivity (TFP). Agricultural TFP serves as the dependent variable, while agricultural insurance is the core independent variable. To explore the underlying mechanisms, country governance and moral hazard are incorporated as moderating variables. In addition, a set of other independent variables is included to account for other determinants of agricultural TFP, including agricultural structure, disaster impact, rural human capital, urbanization rate, agricultural mechanization level, and rural residents' per capita disposable income. The specific definitions of these variables are presented below:

3.3.1 Dependent Variable

The dependent variable selected for this study is agricultural total factor productivity. This is due to the fact that agricultural total factor productivity is the core indicator for measuring agricultural development. Compared to a single indicator (such as output or value added), it can more comprehensively and scientifically reflect the overall efficiency improvement and technological progress of the agricultural system; agricultural total factor productivity can eliminate the growth solely resulting from an increase in input scale, and more accurately reflect the quality of agricultural development (Zhang et al., 2025). Agricultural total factor production was also used by Kryszak and Wicki (2023) and Hassan et al. (2023) to gauge the degree of agricultural progress.

3.3.2 Independent Variables for Baseline Regression Analysis

The core independent variable of this study is selected as the per capita agricultural insurance premium income to measure the development level of agricultural insurance. The reason is that the per capita premium income can reflect the average investment made by each person in agricultural insurance (Jin et al., 2022). The higher the value, the wider the coverage of agricultural insurance in the population and more farmers participate in agricultural insurance. The premium income of agricultural insurance is the basis for insurance companies to provide risk protection. A higher per capita premium income means that the insurance companies have more funds available for compensation, which can provide stronger risk protection for farmers (Liu, 2025).

In the academic community, there is no consensus on the measurement standards for the development level of agricultural insurance. Most scholars use per capita

agricultural insurance premium income to measure the development level of agricultural insurance (Li, 2022; Smith and Glauber, 2012; Zhou, 2022). Some scholars use insurance income of each province in China to measure the development level of agricultural insurance (Gong, 2021). This study uses per capita agricultural insurance premium as an indicator to measure the development level of agricultural insurance, where per capita agricultural insurance premium is equivalent to agricultural insurance premium income or primary industry employees. The reason is that the service targets of agricultural insurance are the population engaged in agricultural production (i.e., primary industry employees). Dividing the agricultural insurance premium income by the number of this group of people can directly reflect the average insurance cost borne by each agricultural practitioner, and more accurately reflect the coverage and investment of agricultural insurance in the target group (Li, 2025).

Control variables are as follows:

i. The Agricultural Structure

This variable is measured by the ratio of grain sown area to the total sown area of crops (%), reflecting the relative emphasis on staple crops within the overall agricultural system. Adjusting the agricultural structure can help better align production with market demand, improve resource allocation efficiency, and ultimately promote improvements in agricultural total factor productivity. As noted by Jin (2022), and supported by international studies (Alene & Coulibaly, 2009), optimizing crop composition through structural adjustment is a key strategy for enhancing agricultural productivity, particularly when combined with technological progress and input efficiency. Therefore, agricultural structure is selected as an important independent variable in the model.

ii. Disaster Impact

Disaster impact is calculated by dividing the area of crops affected by the disaster by the total area of crops sown. Disaster impact is used to capture the adverse environmental and climatic conditions affecting agricultural production. Natural disasters such as floods, droughts, pests, and extreme weather events can damage agricultural infrastructure, reduce yields, lower farm incomes, and dampen farmers' production incentives. These negative effects hinder improvements in agricultural productivity and constrain agricultural economic growth. In line with Jin (2022) and the findings of Kumar and Khanna (2021), disaster impact is included as an independent variable to reflect the role of environmental shocks in influencing total factor productivity in agriculture.

iii. Rural Human Capital

Rural human capital is measured using the logarithm of the average years of schooling of rural household labor. Following Zhu (2022), the education level of farmers is used as a proxy for human capital. A higher level of education improves farmers' ability to access, process, and apply information, which increases their likelihood of adopting new technologies and optimizing the allocation of production inputs. This, in turn, contributes to the enhancement of agricultural total factor productivity. As Foster and Rosenzweig (2010) emphasize, education plays a critical role in overcoming informational and behavioral barriers to the adoption of modern agricultural technologies in developing economies.

In this study, rural human capital (Hum) is calculated as a weighted average of educational attainment across the rural population:

$$\mathrm{Hum}=\mathrm{prim}\times 6+\mathrm{midd}\times 9+\mathrm{high}\times 12+\mathrm{univ}\times 16 \qquad \text{Equation 3.1}$$

Based on equation 3.1, Hum represents Rural Human Capital, where prim, midd, high, and univ represent the proportions of rural residents with primary, middle school, high school, and college-level education, respectively. This formulation captures the cumulative effect of education on productivity-enhancing behavior in agricultural households.

iv. Urbanization Rate

The urbanization rate is measured by the proportion of the urban population to the total population (%), following the approach of Jin (2022). This indicator reflects the overall level of local economic and social development. A rising urbanization rate can lead to improvements in infrastructure, market expansion, and enhanced flows of information, capital, and technology. These changes are conducive to the adoption of modern agricultural technologies, better allocation of agricultural production factors, and ultimately the enhancement of agricultural total factor productivity. Empirical evidence from Zhou et al. (2019) supports this view, showing that urbanization in China has produced positive spillover effects on agricultural productivity through increased resource integration and technological diffusion.

v. The Power Level

The power level is measured using rural electricity consumption, which serves as a proxy for the development of agricultural infrastructure. A higher level of electricity access reflects better infrastructure for irrigation, storage, mechanized farming, and other energy-dependent agricultural processes. According to Zhou (2022), electricity availability is crucial for enhancing farmers' capacity to adopt modern production technologies and reduce reliance on manual labor, thereby improving efficiency and productivity.

This view is echoed in the findings of Nwachukwu and Egwu (2017), who empirically show that electricity consumption significantly contributes to agricultural productivity by enabling mechanization in rural Nigeria. Similarly, Adams and Klobodu (2019) find a positive long-term relationship between energy infrastructure—both renewable and non-renewable—and agricultural total factor productivity in sub-Saharan Africa. Therefore, electricity access is considered a vital determinant of agricultural modernization and TFP growth.

vi. Per Capita Disposable Income of Rural Residents

Per capita disposable income of rural residents is used as a control variable to reflect the income level of rural households. Following Zhu (2022), this variable is expressed in logarithmic form to account for heteroscedasticity and nonlinear effects. Higher levels of rural income may facilitate investment in agricultural inputs, adoption of new technologies, and improved farm management, all of which are positively associated with agricultural total factor productivity. The variable definitions are presented in Table 3.1.

Table 3.1: Variable Definitions and Data Sources

Variable	Definition / Proxy	Unit	Data Source	Representative Studies
Agricultural TFP	Agricultural total factor productivity measured using the DEA–Malmquist	Index	National Bureau of Statistics of China; China Rural Statistical Yearbook	Gao et al. (2023)
Agricultural Insurance	Agricultural insurance premium income per rural resident (insurance premium density)	Yuan/person (logarithm)	China Insurance Statistical Yearbook	Wen et al. (2023)
Country Governance	governance quality index	Index	World Bank Worldwide Governance Indicators	World Bank (2023)
Moral Hazard	The amount of fertilizer used per 100,000 hectares of sown area	Ten thousand tons	China Rural Statistical Yearbook	Durandish et al.(2023)
Per capita disposable income of rural residents	Average disposable income available to rural residents	Yuan/person	China Rural Statistical Yearbook	Bhuiyan et al. (2022)
The power level	Electricity consumption of rural residents	Billion kilowatt-hours (logarithm)	China Rural Statistical Yearbook	Zhou. (2022)
Urbanization rate	Share of urban population in total population	%	China Statistical Yearbook	Jin. (2022)
Rural human capital	Average years of education of the rural labor force	Years (logarithm)	China Population & Employment Statistical Yearbook	Zhu. (2022)
Disaster impact	Share of damaged crop area in total sown area	%	China Rural Statistical Yearbook	World Bank (2019)
Agricultural structure	Share of grain sown area in total crop sown area	%	China Rural Statistical Yearbook	Gao et al. (2023)

3.3.3 Moderating Variables

3.3.3.1 Moral Hazard

Moral hazard was first defined in the context of insurance by Arrow (1963), which was defined as that the insured reduces motivation and efforts to prevent insurance accidents due to the purchase of insurance protection, so as to obtain insurance compensation exceeding expectations. Moral hazard is widespread in the insurance industry, especially in the agricultural insurance sector. Yuan (2024) proposed that due to the information asymmetry in agricultural production, the moral hazard incentive measures in agricultural insurance would cause farmers who take out insurance to reduce production inputs, such as reducing disaster prevention expenditures like fertilizers and pesticides. Durandish et al. (2023) and Rosalia (2023) found that after farmers purchased crop insurance, some would plant crops on poor land. At the same time, the use of production inputs such as fertilizers would also decrease, thereby increasing insurance costs.

Wang et al. (2017) conducted an empirical analysis of information asymmetry in agricultural insurance in China using regional underwriting summary data from 10 property insurance companies in the country from 2007 to 2014, and confirmed the existence of a certain degree of moral hazard. Hao (2023) pointed out that the development of agricultural insurance inevitably encounters problems of moral hazard and adverse selection. Fu et al. (2024) found that agricultural insurance can effectively promote the rational allocation of agricultural production factors, thereby increasing agricultural output and promoting the improvement of agricultural total factor productivity. Lu (2023) found that the boosting effect of agricultural insurance on agricultural total factor productivity is achieved through technological progress and technical efficiency.

In summary, moral hazard undermines the effective functioning of agricultural insurance by distorting farmers' risk management incentives (Goodwin & Smith, 2013). Weakened insurance performance, in turn, limits the scheme's capacity to stabilise income, encourage technology adoption, and facilitate an efficient re allocation of production inputs—key channels through which agricultural insurance can boost agricultural total factor productivity (Glauber, 2004). Consequently, the overall effect of moral hazard on agricultural TFP is indirect: it operates by eroding the developmental impact that well-functioning agricultural insurance would otherwise exert on productivity.

Summarized evidence from recent empirical studies indicates that farmer participation in agricultural insurance often gives rise to moral-hazard behavior, which in turn alters input decisions — notably the intensity of agrochemical use. Several recent studies find that insured farmers may reduce costly inputs (fertilizer or pesticides) because insurance partially shields them from downside risk, leading to lower ex-post incentives to maintain previous input levels (Yuan, 2024; Durandish, 2023; Rosalia, 2023). Based on these findings, this study treats moral hazard as a moderating variable and measures its degree by the amount of fertilizer used per 100,000 hectares of sown area. Operationally, lower the amount of fertilizer used per 100,000 hectares of sown area is interpreted as a higher likelihood (or degree) of moral hazard induced by insurance coverage, while higher the amount of fertilizer used per 100,000 hectares of sown area implies a lower likelihood of moral-hazard behavior. Using fertilizer intensity as the proxy allows the analysis to capture how insurance-induced behavioral changes in input application moderate the effect of agricultural insurance on agricultural total factor productivity (TFP).

3.3.3.2 Country Governance

According to Kaufmann et al. (2011), governance is "the traditions and institutions by which authority in a country is exercised." This includes the procedures used to choose, oversee, and replace governments; the ability of the government to create and carry out sensible policies; and the regard that the public and the government have for the institutions that regulate social and economic interactions. The rule of law, political stability and the absence of terrorism or violence, corruption control, voice and accountability, government efficacy, and regulatory quality are the six characteristics of governance that are measured by the Worldwide Governance Indicators (WGI) framework.

Data from the World Bank's Global Governance Indicators database was used to measure the level of governance in China. This database was established by Kaufmann et al. (2011). The indicators in the database are drawn from governance indicators of more than 200 countries and territories, and the database is updated annually to reflect the views of business information promoters, non-governmental organizations, public sector organizations and survey respondents.

China's agricultural insurance system is predominantly policy-based, meaning that its development is closely tied to direct government involvement and support (Huang, 2023). The government plays a crucial role by offering policy incentives and substantial financial subsidies to promote the adoption and expansion of agricultural insurance programs. Given this institutional context, the effectiveness and quality of national governance significantly influence how agricultural insurance policies are formulated, implemented, and monitored. Therefore, this study incorporates country governance as a

moderating variable to examine how the quality of governance may condition the effect of agricultural insurance on agricultural total factor productivity (Zheng et al., 2020).

Country governance serves as a moderating variable in this study, influencing the relationship between the development of agricultural insurance and agricultural productivity in China. Among the various dimensions of governance, government effectiveness is most commonly employed by scholars as a proxy for national governance quality (Gani, 2012; Cahan et al., 2016; Ilhan, 2022). Government effectiveness captures the quality of public services, the capacity of civil servants, and the credibility of policy implementation, all of which are critical for the successful execution of policy-based agricultural insurance. Accordingly, this study adopts government effectiveness as the primary indicator to measure the level of country governance in China. Descriptive statistics for the moderating variable are presented in Table 3.1.

3.4 Malmquist Productivity Index (MPI) for Calculating Provinces Productivity of Agriculture

In measuring the agricultural productivity, economic growth accounting method and index method were mainly used in the early days. These methods must meet the premise of complete efficiency, but in the actual situation, manufacturers in less developed countries and regions are prone to non-efficiency, so that the actual productivity is not consistent with the optimal productivity, so the early measurement methods have major defects (Coelli et al., 2004).

Based on this, subsequent researchers changed the assumption to allow for inefficiency and proposed stochastic frontier Analysis (SFA), which decomposed agricultural productivity into technical progress and technical efficiency (Aigner et al.,

1977). However, the accuracy of the estimation results of this method depends on the precision of the preset production function, and there are still some problems in the application process (Greene, 2008).

Subsequent researchers combined Malmquist index with DEA model to propose DEA-Malmquist index method, which overcame the shortcomings of parameter estimation method well and was widely used, thus further improving the agricultural productivity theory. The Malmquist index was first introduced by Swedish economist Malmquist (1953). The researcher developed it as a way to measure changes in consumer welfare between two time periods. Malmquist (1953) used distance functions in a multi-output context to compare the consumption possibilities of two different consumption bundles. However, his initial work was mainly in the context of consumer theory and did not have an immediate application in production analysis.

In the 1980s, researchers began to adopt the Malmquist index for the analysis of productivity changes in production processes. The combination of the Malmquist index with DEA was a significant development. The first DEA model was the CCR model, which assumed constant returns to scale. The DEA model was developed by Charnes et al. (1978), is a non - parametric method for evaluating the relative efficiency of decision - making units (DMUs) that use multiple inputs to produce multiple outputs. Their seminal work introduced the basic concept and methodology of DEA, presenting it as a non-parametric approach to measure the relative efficiency of decision-making units (DMUs) that use multiple inputs to produce multiple outputs.

DEA is designed to evaluate the relative efficiency of Decision Making Units (DMUs) that use multiple inputs to produce multiple outputs. For each DMU, these inputs

and outputs must be clearly identified and quantified. The DMUs being compared should be homogeneous in nature, meaning they should be engaged in similar activities or production processes. Sufficient and accurate data on inputs and outputs for each DMU are essential (Cooper et al., 2011). Errors or missing values in the data can lead to inaccurate efficiency evaluations. Unlike parametric methods such as the production function approach, DEA does not require a pre-specified functional form between inputs and outputs. This also means that there should be no prior assumptions about the exact mathematical relationship between the variables (Thanassoulis, 2001).

Banker et al. (1984) extended the DEA framework by introducing the BCC model which made important contributions to the development of DEA. This model relaxed the constant returns to scale assumption of the CCR model, allowing for the analysis of variable returns to scale and separating technical efficiency into pure technical efficiency and scale efficiency. Over the years, numerous theoretical refinements have been made to enhance the flexibility and accuracy of DEA models. Researchers have explored alternative distance functions—such as input-oriented, output-oriented, and non-radial measures like the slacks-based model—to better reflect the nature of production processes and inefficiency (Tone, 2001). Additionally, methods have been developed to accommodate undesirable outputs in the production set (Färe et al., 1993) and to incorporate weight restrictions that reflect managerial preferences or policy considerations (Allen et al., 1997).

In the 1980s and 1990s, Data Envelopment Analysis (DEA) began to be widely applied across various sectors. In the banking industry, it was used to evaluate the operational efficiency of financial institutions and identify potential areas for improvement (Berger & Humphrey, 1997). In agriculture, DEA was increasingly adopted to analyze

farm-level productivity and efficiency, particularly in developing countries where conventional parametric methods were limited (Bravo-Ureta & Pinheiro, 1993).

Among DEA-based methodologies, the Malmquist productivity index has received significant attention for its ability to measure changes in total factor productivity (TFP) over time. This approach enables the decomposition of productivity changes into components of technical efficiency and technological progress, and it has been extensively applied to assess agricultural TFP growth, compare regional performance, and evaluate the contribution of innovation to agricultural development (Coelli et al., 2005). In the manufacturing sector, it is commonly employed to examine firm-level productivity changes, assess the effects of technological innovation and managerial practices, and guide resource reallocation strategies (Färe et al., 1994). DEA and Malmquist methods have also found wide applications in service industries such as banking and healthcare, where they are used to track performance, benchmark against best practices, and analyze productivity dynamics (Hollingsworth, 2003).

Over the years, there have been numerous theoretical refinements to the Malmquist-DEA approach. For example, different types of distance functions (input-oriented, output-oriented, and non-radial) have been explored to better capture the nature of production and efficiency changes (Coelli et al., 2005). Researchers have also studied how to handle issues such as variable returns to scale and the choice of appropriate inputs and outputs more rigorously (Dyson et al., 2001). In summary, the Malmquist - DEA methodology has evolved from its origins in consumer welfare analysis to a widely - used and continuously evolving tool in productivity analysis across a broad range of industries

and research areas. Therefore, this research adopts DEA-Malmquist index method to calculate agricultural productivity (Zhang, 2023).

Agricultural productivity in this study is calculated using DEA-Malmquist index method. Table 3.2 shows the list of input and output used in the calculation of agricultural total factor productivity. This study takes the added value of agricultural as the agricultural output variable. Here, the added value of agricultural is used instead of the total output value or agricultural output value of agriculture, forestry, animal husbandry, and fishery, because the added value of agricultural can more accurately reflect the output level (Tang, et al., 2022). The relevant methods can be referred to in Zheng and Li (2022) and Zeng and Zhang (2022) who calculated the agricultural total factor productivity by using the added value of agricultural. In terms of the selection of agricultural production input, Ye et al. (2025) and Fuglie (2018) used five commonly used indicators as input in this research: labor input, sown area, mechanical input, fertilizer input, and irrigation area. Considering the multicollinearity of irrigation area and crop sown area, this study finally selected four indicators including labor input, land input, mechanical input, and fertilizer input to estimate the agricultural total factor growth rate, which are consistent with the indicators used by Latruffe (2017) and Zhou (2022) to calculate the agricultural total factor productivity. The selection of variables and the descriptive statistical results of inputs and outputs are presented in Table 3.2.

Table 3.2: Descriptive Statistics of Agricultural Total Factor Productivity Estimation Based on DEA-Malmquist Productivity Index

Variable Type	Variable name	Unit	Mean	Standard Deviation	Minimum	Maximum
Input variables	Primary industry practitioners	10,000 peoples	778.637	580.411	20.000	2,920.000
	Total sown area of crops	Thousand hectares	5,301.332	3808.404	88.600	15,304.220
	Total power of agricultural machinery	Million kilowatts	3,225.670	2,888.284	94.000	13,353.000
	Agricultural fertilizer application	Ten thousand tons	178.807	142.366	2.796	716.100
Output variables	Primary industry added value	Billion RMB	1,923.926	1,471.440	54.890	6,506.200

From the table, the descriptive statistics for the input and output variables used in the calculation of agricultural TFP in China provinces are shown. The agricultural output variable is provided by the added value of the primary industry, which closely reflects the level of agricultural output. The input variables are the primary industry practitioners (labor), total sown area of crops, total power of agricultural machinery and the agricultural fertilizer application. The selection of input variables for estimating agricultural TFP follow Zhou (2015), Jin (2022) and Fuglie (2018).

The applications of DEA-Malmquist index to calculate agricultural total factor productivity has several advantages. First, does not need to pre-set the functional form of the model and assume the random distribution of the error term, which can effectively avoid the bias caused by the setting of production function equation, and can better solve the problem of multi-input and multi-output in the calculation of agricultural total factor

productivity (Coelli et al., 2005). Second, the calculation process is simple and has been incorporated into the research system by most scholars recently (Chaubey et al., 2022). Therefore, the DEA-Malmquist index method is selected for the calculation of agricultural total factor productivity in this study.

This study uses MaxDEA software to estimate the changes of agricultural total factor productivity in China and various provinces based on DEA-Malmquist index approach. MaxDEA is a data envelopment analysis software, which has high-speed computing power and parallel processing ability, and has advanced algorithms and strict data validation in the process of data processing to avoid the generation of wrong data (Jablonský, 2025).

The DEA-Malmquist index method, under the assumption of constant returns to scale (CRS), the Malmquist productivity index measured by this method can be decomposed into technical efficiency and technical progress by common formula as reflected in Equation 3.2 below:

$$\begin{aligned} M_i(x_{t+1}, y_{t+1}, x_t, y_t) &= \left[\frac{D_i^t(x_{t+1}, y_{t+1})}{D_i^t(x_t, y_t)} \times \frac{D_i^{t+1}(x_{t+1}, y_{t+1})}{D_i^{t+1}(x_t, y_t)}\right]^{1/2} \\ &= \frac{D_i^{t+1}(x_{t+1}, y_{t+1})}{D_i^t(x_t, y_t)} \times \left[\frac{D_i^{\mathrm{t}}(x_t, y_t)}{D_i^{t+1}(x_t, y_t)} \times \frac{D_i^{\mathrm{t}}(x_{t+1}, y_{t+1})}{D_i^{t+1}(x_{t+1}, y_{t+1})}\right]^{1/2} \end{aligned} \quad \text{Equation 3.2}$$

Based on equation 3.2, $M_i(x_{t+1}, y_{t+1}, x_t, y_t)$ represents the TFP of the production point (x_{t+1}, y_{t+1}) relative to the production point (x_t, y_t). (x,y) represents input and output vectors. *Di* represents the input-oriented distance function, that is, how to adjust the input elements to better match the optimal input under the assumption that the output does not change. The formula converts the change in TFP into the product of changes in technical

efficiency and technological progress. The former represents the change in technical efficiency of the *ith* decision unit from *T* to *T+1*, while the latter item represents the geometric mean of the change in production technology from *T* to *T+1* of the same decision unit, which means the movement of the production frontier boundary. Therefore, the TFP change index measured by this method can be decomposed into two items, namely the technical efficiency change index (EC) and the technological progress index (TC), which are expressed by the formula in Equation 3.3:

$$M_1(x_{t+1}, y_{t+1}, x_t, y_t) = EC_i^{t+1} \times TC_i^{t+1} \qquad \text{Equation 3.3}$$

The movement of TFP from t to $t+1$ is measured by comparing the Malmquist index above to 1.

If the index is greater than 1, it means that the TFP from t to $t+1$ shows positive growth; If the index is equal to 1, it indicates that the TFP from t to $t+1$ remains unchanged; If the index is less than 1, it indicates that TFP from t to $t+1$ shows negative growth. Similarly, the descriptions of its decomposition index are similar to this.

3.5 Empirical Approaches for Analyzing the Impact of Agricultural Insurance on Agricultural Total Factor Productivity

3.5.1 Panel Data Analysis

Panel data refers to data that tracks the same group of individuals over a period of time. It has both a cross-sectional dimension (n individuals) and a time dimension (T periods). In a panel model, if the explanatory variables include the lagged values of the explained variable, it is called a dynamic panel; otherwise, it is called a static panel. If the

individuals in the sample are exactly the same in each period of the panel data, it is called balanced panel data; otherwise, it is called unbalanced panel data (Rüttenauer & Kapelle, 2024).

The main advantages of panel data are as follows: First, it can solve the problem of omitted variables. Omitted variable bias is a common problem. Although it can be addressed using instrumental variable methods, effective instrumental variables are often difficult to find. Second, it provides more information on the dynamic behavior of individuals. Since panel data has both cross-sectional and time dimensions, it can sometimes solve problems that cannot be solved by separate cross-sectional or time series data. Third, it has a larger sample size. Due to the presence of both cross-sectional and time dimensions, the sample size of panel data is usually larger, thereby providing greater estimation accuracy (Zyphur et al., 2020). Therefore, this study chose to use panel data for the analysis.

3.5.2 Diagnostic Tests for Baseline Regression Assumptions

To ensure that the pooled OLS, fixed effects, and random effects models satisfy the assumptions of baseline regression and to guarantee reliable statistical inference, a comprehensive set of diagnostic tests is conducted following standard panel data econometric practice (Wooldridge, 2002, 2010; Greene, 2018). These tests address heteroscedasticity, serial correlation, cross-sectional dependence, and multicollinearity, which commonly arise in panel data applications.

i. Heteroscedasticity

Assumption, the baseline regression model assumes homoscedastic disturbances, meaning that the variance of the error term is constant across cross-sectional units and over time (White, 1980).

Tests employed, heteroscedasticity is examined using the Breusch–Pagan test for the pooled OLS model (Breusch & Pagan, 1979) and the modified Wald test for groupwise heteroscedasticity in the fixed effects model, as recommended for panel data settings (Greene, 2018).

Interpretation, in both tests, the null hypothesis is homoscedasticity. Rejection of the null indicates the presence of heteroscedasticity, which may render conventional standard errors inconsistent (White, 1980).

Corrective measure, to address this issue, heteroscedasticity-robust standard errors are employed. In the panel setting, standard errors are clustered at the cross-sectional level to ensure consistent statistical inference (Arellano, 1987; Wooldridge, 2010).

ii. Serial Correlation

Assumption, error terms are assumed to be serially uncorrelated within each cross-sectional unit over time.

Test employed, serial correlation is tested using the Wooldridge test for autocorrelation in panel data, which is widely applied in FE and RE models (Wooldridge, 2002).

Interpretation, the null hypothesis is the absence of first-order serial correlation. Rejection of the null suggests that disturbances are correlated over time, which can bias standard errors and invalidate hypothesis testing (Wooldridge, 2010).

Corrective measure, cluster-robust standard errors are adopted, as they are robust to both heteroscedasticity and within-panel serial correlation (Arellano, 1987; Wooldridge, 2010).

iii. Cross-Sectional Dependence

Assumption, classical panel models assume cross-sectional independence, implying that shocks affecting one cross-sectional unit do not contemporaneously affect others.

Test employed, cross-sectional dependence is examined using Pesaran's CD test, which is suitable for panels with large cross-sectional dimensions (Pesaran, 2004, 2015).

Interpretation, the null hypothesis of the CD test is cross-sectional independence. Rejection indicates the presence of common shocks or spillover effects across regions, a common feature of regional and macro-level panel data (Pesaran, 2004).

Corrective measure, to account for cross-sectional dependence, Driscoll – Kraay standard errors are employed, as they are robust to heteroscedasticity, serial correlation, and cross-sectional dependence in panel data models (Driscoll & Kraay, 1998).

iv. Multicollinearity

Assumption, explanatory variables are assumed not to exhibit perfect or severe multicollinearity.

Tests employed, multicollinearity is assessed using a pairwise correlation matrix as a preliminary diagnostic and the Variance Inflation Factor (VIF) as a formal test (Greene, 2018).

Interpretation, while the correlation matrix provides an initial indication of linear relationships between regressors, VIF values quantify the extent of multicollinearity arising from joint explanatory power. VIF values below the commonly accepted threshold of 10 (and preferably below 5) suggest that multicollinearity is not a serious concern (Greene, 2018).

Overall, the diagnostic tests indicate that some baseline regression assumptions are violated, which is typical in panel data applications. However, by employing robust and appropriately adjusted standard errors — specifically clustered and Driscoll – Kraay corrections—the POLS, FE, and RE estimators yield consistent coefficient estimates and reliable statistical inference (Driscoll & Kraay, 1998; Wooldridge, 2010).

v. Hausman Test

Purpose of the Hausman Test, in panel data analysis, an important methodological issue is the choice between the fixed effects (FE) model and the random effects (RE) model. The Hausman test (Hausman, 1978) is employed to examine whether the individual-specific effects are correlated with the explanatory variables. This test provides a formal statistical criterion for selecting between the FE and RE estimators.

If the unobserved individual effects are correlated with the regressors, the RE estimator becomes inconsistent, whereas the FE estimator remains consistent. Conversely,

if such correlation is absent, the RE estimator is both consistent and more efficient than the FE estimator.

The Hausman test is based on the following hypotheses:

Null hypothesis (H0): The random effects estimator is consistent and efficient; that is, the individual-specific effects are uncorrelated with the explanatory variables.

Alternative hypothesis (H1): The random effects estimator is inconsistent due to correlation between the individual-specific effects and the explanatory variables; in this case, the fixed effects estimator is preferred.

The Hausman test statistic is constructed as:

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})'\left[\mathrm{Var}(\hat{\beta}_{FE}) - \mathrm{Var}(\hat{\beta}_{RE})\right]^{-1}(\hat{\beta}_{RE} - \hat{\beta}_{FE}) \qquad \text{Equation 3.4}$$

The explanation of formulas in Equation 3.4 is as follows. Where $\hat{\beta}_{RE}$ is the coefficient vector estimated by the fixed effects model;. $\hat{\beta}_{FE}$ is the coefficient vector estimated by the random effects model; $\mathrm{Var}(\hat{\beta}_{FE})$ and $\mathrm{Var}(\hat{\beta}_{RE})$ are the corresponding variance–covariance matrices; $(\cdot)'$denotes the transpose of a vector.

Under the null hypothesis, the test statistic asymptotically follows a chi-square ($\chi 2$) distribution, with degrees of freedom equal to the number of regressors being tested.

Decision rule: If the test statistic is statistically significant (i.e., the p-value is below the chosen significance level, such as 1%, 5%, or 10%), the null hypothesis is rejected. This indicates that the RE estimator is inconsistent, and the FE model should be adopted.

If the test statistic is not statistically significant, the null hypothesis cannot be rejected, suggesting that the RE estimator is appropriate and more efficient than the FE estimator.

3.5.3 Baseline Regression Analysis

In this thesis, estimators of Pooled OLS, Fixed Effects (FE) and Random Effects (RE) are used to estimate the static model. Pooled OLS treats panel data as cross - sectional data, ignoring the individual and time heterogeneities, and directly regresses on all observations. It is applicable to situations where the differences among individuals are small or the time effects are not obvious. The model satisfies the classical linear regression assumptions (such as independent and identically distributed error terms, no multicollinearity, etc.). Ceesay and Moussa (2022) pointed out that the advantage of Pooled OLS is its simplicity and ease of use, but it ignores the individual and time heterogeneities of panel data, which may lead to estimation bias. Wooldridge (2010) emphasized that the applicability of Pooled OLS is limited, especially when individual effects are significant. Li and Ye (2012) mentioned that the estimation results of Pooled OLS may be biased due to ignoring individual effects, and it is recommended to be used in preliminary analysis.

By integrating cross-sectional and time-series dimensions, panel data enables researchers to account for unobserved variation among people or entities. The FE and RE models are two popular econometric techniques for panel data analysis. Both are intended to increase the precision of regression estimates and manage heterogeneity in longitudinal datasets (Baltagi, 2008).

In terms of advantages, the FE model controls unobservable individual heterogeneity. It can capture individual characteristics that do not change over time (such as corporate culture, regional culture, personal ability, etc.), and by eliminating individual fixed effects, it avoids omitted variable bias (Greene, 2012). Secondly, it allows individual effects to be correlated with explanatory variables. When unobservable individual characteristics are correlated with the explanatory variables in the model, the FE can provide consistent estimates, which is a key advantage compared to the random effects model (Wang, 2024).

However, one of the disadvantages of FE model is that it cannot estimate the effects of variables that do not change over time. Variables such as gender, race, and geographical location that are time-invariant will be differenced out, and the coefficients of these variables cannot be identified (Angrist & Pischke, 2009). Secondly, it may amplify the measurement error problem. Group-level transformations may increase the proportion of measurement errors relative to the signal (Gao, 2024).

Because the FE model controls individual or time-invariant characteristics by introducing dummy variables for individuals or time, it eliminates the influence of individual or time heterogeneity on the estimation results (Wooldridge, 2010). Following Liu et al. (2024), this study uses the fixed effects model for in the analysis on the impact of agricultural insurance on agricultural TFP in China provinces.

As for RE model, one major advantage is that it takes into account individual heterogeneity but is more efficient. Assuming that individual effects are not correlated with explanatory variables, the generalized least squares method (GLS) is used for estimation, which is more effective (with smaller variance) than the FE method. Secondly, it can

estimate variables that do not change over time. Unlike FE, RE does not eliminate individual variation, so it can estimate the impact of time-invariant variables (such as gender, race, geographical location, etc.) (Kanters, 2021).

Among the disadvantages of the RE model is that the key assumption is strong, assuming that individual effects are not correlated with explanatory variables. Secondly, it is sensitive to heteroscedasticity and autocorrelation. If there is heteroscedasticity or autocorrelation, the estimation results will be inaccurate (Zhang, 2015). Follow Jin (2022), this study compares the RE model with the FE model.

Because of pooled OLS regression, this method does not consider individual heterogeneity, resulting in significant estimation bias; the basic assumption of random regression treats individual effects as random variables, assuming that individual effects are not associated with the explanatory variables (Ceesay & Moussa, 2022). This method ignores unobservable or omitted heterogeneity between individuals, which may be related to the explanatory variables, thereby making the estimates inconsistent. To address this shortcoming, we perform fixed effects model estimation following Zhu (2022). For the baseline analysis, this study performs pooled OLS regression, fixed effects and random effects estimates to provide general pictures on the relationship between agricultural insurance development and agricultural productivity in China provinces.

The baseline regression models for agricultural total factor productivity of China provinces are as follows:

Fixed effects regression model:

$$AGRTFP_{i,t} = \beta_0 + \beta_1 IN_{i,t} + \beta X + \mu_i + \gamma_t + \varepsilon_{it} \qquad \text{Equation 3.5}$$

Random effects regression model:

$$AGRTFP_{i,t} = \beta_0 + \beta_1 IN_{i,t} + \beta X + \mu_i + \varepsilon_{it} \quad \text{Equation 3.6}$$

Pooled OLS regression model:

$$AGRTFP_{i,t} = \beta_0 + \beta_1 IN_{i,t} + \beta X + \varepsilon_{it} \quad \text{Equation 3.7}$$

The explanation of formulas in Equation 3.5 to 3.7 is as follows. Where i is the province, t is the year, $AGRTFP_{i,t}$ is the agricultural total factor productivity, $IN_{i,t}$ is the agricultural insurance, X is a vector of control variables including the agricultural structure, disaster impact, rural human capital, urbanization rate, the power level, pei capita disposable income of rural residents, β_0 is the constant term, β_1 is parameters to be estimated, β is the column vector of control variables, μ_i is the fixed effect of province, γ_t is the time fixed effect, and ε_{it} is the disturbance term. In the random effects regression model, μ_i is no correlation with explanatory variables.

3.5.4 Steps for Robustness Test of the Baseline Regression Analysis

Since the fixed effects model controls for specific characteristics of individuals or time through the introduction of dummy variables for these characteristics that remain constant over time or across individuals, it can eliminate the influence of individual or time differences on the estimation results. Therefore, this study takes the regression results of the fixed effects model as the standard. In order to further verify the accuracy of the results of fixed effects model regression analysis, the following four methods are planned to be used for reference to the processing methods of existing studies to test the robustness of the results.

i. Province-clustered Standard Error

Due to different provinces, there may be some differences in the interference factors affecting productivity, which brings a certain degree of heteroscedasticity problem, and the correlation of productivity in time leads to the intra-group autocorrelation problem of panel data. We use the clustering robust standard error at the provincial level to re-estimate the model. In order to mitigate the coefficient significance bias caused by heteroscedasticity and autocorrelation problems. Wu and Xu (2024) suggest robustness test using the clustering robust standard error method.

ii. Replace Independent Variables

In the fixed effects model analysis, this study used per capita insurance premium as an independent variable to measure the development level of regional agricultural insurance from the perspective of income. Next, this study replaced the independent variable with the loss rate of agricultural insurance to measure the development level of agricultural insurance from the perspective of expenditure. The loss rate of agricultural insurance has been widely used in the literature as an indicator of insurance effectiveness, as it reflects the extent to which insurance payouts compensate for realized agricultural risks and stabilize farmers' income in the presence of shocks (Hazell et al., 2010). From the perspective of agricultural risk management theory, effective compensation mechanisms — rather than insurance scale alone — are critical for reducing production uncertainty and influencing farmers' investment and input decisions. Therefore, the loss rate can serve as a meaningful proxy for the functional intensity of agricultural insurance.

In empirical research, employing both premium-based and loss-rate-based indicators is considered a valid robustness strategy to test whether the estimated effects of

agricultural insurance on productivity are sensitive to alternative measures of insurance development and effectiveness (Cai et al., 2020; Tang et al., 2022). If the core results under these indicators remain consistent, this will further enhance the robustness and reliability of the conclusions of this paper. Therefore, it is reasonable for this study to only take the agricultural insurance loss rate as a robustness test indicator. In reference to Tang et al (2022), the compensation amount of agricultural insurance was selected to replace the development level of agricultural insurance in the sample for robustness test.

iii. Replace the Dependent Variables

In the fixed effects model analysis, this study calculate the multiplicative of the agricultural productivity index as agricultural total factor productivity, similarly, we also use the multiplicative of the technical efficiency index (EC) as a substitute for agricultural total factor productivity to reflect the efficiency changes brought about by technological change. Reference Zhou (2022) replace the dependent variables for robustness test.

iv. Remove Suspicious Samples

Considering the impact of epidemic factors, the production, transportation and sales of most agricultural products stopped during the epidemic period (2020-2023), which greatly interfered with agricultural productivity. Secondly, to ensure the continuity of sample period, we excluded samples from 2020 and later. Refer to Cheng and He (2024) to eliminate suspicious samples for robustness test.

3.5.5 Dynamic Panel Data Analysis Using Generalised Method of Moments Estimations

The Generalized Method of Moments (GMM) estimation was formalized by Hansen (1982), and since has become one of the most widely used methods of estimation for models in economics and finance. Unlike the maximum likelihood estimation (MLE), GMM does not require complete knowledge of the distribution of the data. Only specified moments derived from an underlying model are needed for the GMM estimation. In some cases where the distribution of the data is known, MLE can be computationally very burdensome, whereas GMM can be computationally very easy. The log-normal stochastic volatility model is one example. In models for which there are more moment conditions than model parameters, the GMM estimation provides a straightforward way to test the specification of the proposed model. This is an important feature that is unique to the GMM estimation. Difference GMM and System GMM are two main estimation methods within the GMM framework.

3.5.5.1 Difference GMM

Difference GMM was proposed by Arellano and Bond (1991). It eliminates individual fixed effects by taking the first - order difference of the dynamic panel model and uses lagged variables as instrumental variables to address the endogeneity problem. Difference GMM is suitable for short - panel data, especially when the explanatory variables are endogenous. Arellano and Bond (1991) proposed the Difference GMM estimation method and verified its effectiveness through Monte Carlo simulation and empirical applications. Adilie et al. (2024) conducted a regression analysis using the

dynamic difference GMM model based on the panel data of 14 prefectures in Xinjiang from 2010 to 2020, to study the relationship between environmental regulations and the development of animal husbandry.

3.5.5.2 System GMM

Arellano and Bover (1995) proposed the System GMM (One-Step) method and proved that it is more effective than Difference GMM in estimating dynamic panel models. System GMM combines the difference equation and the level equation. It does not only eliminate individual fixed effects by using the difference equation but also retain the long-term information of the variable levels through the level equation. Compared with using only difference GMM, System GMM comprehensively capture the dynamic characteristics and long-term relationships in the data. Two-Step System GMM was proposed by Blundell and Bond (1998), The Two-Step system GMM first uses the initial weight matrix for a preliminary estimation in the first step, and in the second step, an optimal weight matrix is constructed based on the residuals from the first step to re-estimate and improve efficiency. The Two-Step system GMM is more accurate in estimation than the One-Step system GMM. Cai (2025) constructed a dynamic panel data model using observations from 31 Chinese provinces for the period 2010–2019. Employing the system generalized method of moments, the study examined the effect of basic medical insurance on the development of commercial health insurance, addressing potential endogeneity and dynamic persistence in insurance participation.

Therefore, after comprehensively considering the above situations, this study selects two step System GMM to estimate the impact of agricultural insurance

development on agricultural TFP in China provinces. The model specific was set as follows:

$$AGRTFP_{i,t} = \beta_0 + \beta_1 AGRTFP_{i,t-1} + \beta_2 IN_{i,t} + \beta_k X_{k,i,t} + \varepsilon_{it} \qquad \text{Equation 3.8}$$

Based on the agricultural TFP model in Equation 3.8. Where i is the province, t is the year, $AGRTFP_{i,t}$ is the agricultural total factor productivity, $AGRTFP_{i,t-1}$ is the one-period lag of agricultural total factor productivity, $IN_{i,t}$ is the agricultural insurance, $X_{k,i,t}$ are the data matrix of a series of control variables including the agricultural structure, disaster impact, rural human capital, urbanization rate, the power level, pei capita disposable income of rural residents, β_0 is the constant term, $\beta_1$and β_2 are parameters to be estimated, β_k is the column vector of control variables, where the k th row element is the coefficient of the k control variable, and ε_{it} is the disturbance term.

3.5.5.3 Post-estimation Diagnostic Tests for the GMM

Given the dynamic specification of the model, this study employs the dynamic panel GMM estimator to address potential endogeneity, unobserved individual heterogeneity, and persistence in agricultural total factor productivity. To assess the validity of the GMM estimation, post-estimation diagnostic tests are conducted, with particular attention to serial correlation in the residuals.

Following Arellano and Bond (1991), the Arellano–Bond serial correlation tests are applied to the first-differenced residuals. Two tests are reported:

AR(1) test: The null hypothesis is that there is no first-order serial correlation in the differenced residuals. In dynamic panel models, rejection of the null hypothesis for

AR(1) is expected, as first-differencing induces mechanical first-order correlation even when the original error term is serially uncorrelated.

AR(2) test: The null hypothesis is that there is no second-order serial correlation in the differenced residuals. Failure to reject the AR(2) null hypothesis is essential, because the presence of second-order autocorrelation would invalidate the use of lagged endogenous variables as instruments and render the GMM estimates inconsistent.

The empirical results show that the AR(1) test is statistically significant, while the AR(2) test fails to reject the null hypothesis. This indicates the absence of second-order serial correlation in the residuals, thereby confirming the validity of the moment conditions and supporting the consistency of the GMM estimator.

3.6 Model Specifications for Estimating the Moderating Impacts of Country Governance and Moral Hazard on the Relationship Between Agricultural Insurance Development And Agricultural TFP

3.6.1 Model Specifications using Fixed Effects

This section uses a fixed effects estimation technique to model the relationship between agricultural insurance and agricultural TFP by introducing country governance and moral hazard. Because pooled regression does not consider individual heterogeneity, leading to significant estimation bias. The random effects model treats individual effects as random variables, assuming that individual effects are not associated with the explanatory variables, this method ignores unobservable or omitted heterogeneity between individuals,

which may be related to the explanatory variables, resulting in inconsistent estimates. To address this issue, we conducted fixed effects model estimation.

In order to accurately and systematically examine the impact of agricultural insurance on total factor productivity in agriculture, as well as the moderating effects of country governance and moral hazard, the following models have been constructed:

$$AGRTFP_{i,t} = \beta_0 + \beta_1 IN_{i,t} + \beta_2 CG_{i,t} \times IN_{i,t} + \beta_3 CG_{i,t} + X_{k,i,t}\beta_k + \mu_i + \gamma_t + \varepsilon_{it} \quad \text{Equation 3.9}$$

$$AGRTFP_{i,t} = \beta_0 + \beta_1 IN_{i,t} + \beta_2 MH_{i,t} \times IN_{i,t} + \beta_3 MH_{i,t} + X_{k,i,t}\beta_k + \mu_i + \gamma_t + \varepsilon_{it} \quad \text{Equation 3.10}$$

The explanation of formulas in Equation 3.9 to 3.10 is as follows. Where i is the province, t is the year, $AGRTFP_{i,t}$ is the agricultural total factor productivity, $IN_{i,t}$ is the agricultural insurance, $CG_{i,t}$ is the country governance, $MH_{i,t}$ is the moral hazard, $X_{k,i,t}$ are the data matrix of a series of control variables including the agricultural structure, disaster impact, rural human capital, urbanization rate, the power level, pei capita disposable income of rural residents, β_0 is the constant term, β_1, β_2 and β_3 are parameters to be estimated;, β_k is the column vector of control variables, where the k th row element is the coefficient of the k control variable, μ_i is the fixed effect of province, γ_t is the time fixed effect, and ε_{it} is the disturbance term.

3.6.2 Model Specifications Using Generalised Method of Moments

As the econometric model is a dynamic panel model with endogeneity, in order to make the empirical results more convincing and eliminate the possible influence of

endogeneity, the System Generalized Method of Moment (hereinafter referred to as "system GMM") is adopted to analyze the role of national governance and moral hazard as regulating variables in the process of agricultural insurance's impact on agricultural total factor productivity. At the same time, both the Sargan test and the Hansen test are necessary to examine the validity of the overidentifying restrictions in the GMM estimation. While the Sargan test assumes homoskedasticity, the Hansen test provides a more robust alternative in the presence of heteroskedasticity (Hansen, 1982).

A key consideration when using the System GMM estimator is the number of instruments employed. An excessive number of instruments can overfit the endogenous variables and lead to unreliable Hansen test results—typically indicated by a p-value that is too high (approaching 1), falsely suggesting instrument validity.

Therefore, this study carefully limits the number of instruments used in estimation to avoid the “instrument proliferation” problem and ensure that the Hansen test p-value remains at an acceptable level—neither too high nor too low, thereby providing more credible diagnostic results. The Sargan test results are also reported for completeness, although they are more sensitive to heteroskedasticity and hence used primarily as a supplementary diagnostic tool.

In order to accurately and systematically examine the impact of agricultural insurance on agricultural TFP and the moderating effects of country governance and moral hazard. Following Zhu (2022), the analysis of moderating effects is written as follows:

$$\mathrm{AGRTFP}_{i,t} = \beta_0 + \beta_1 \mathrm{AGRTFP}_{i,t-1} + \beta_2 \mathrm{IN}_{i,t} + \beta_3 \mathrm{CG}_{i,t} \times \mathrm{IN}_{i,t} + \beta_4 \mathrm{CG}_{i,t} + \beta_k \mathrm{X}_{k,i,t} + \varepsilon_{it} \qquad \text{Equation 3.11}$$

$$AGRTFP_{i,t} = \beta_0 + \beta_1 AGRTFP_{i,t-1} + \beta_2 IN_{i,t} + \beta_3 MH_{i,t} \times IN_{i,t} + \beta_4 MH_{i,t} + \beta_k X_{k,i,t} + \varepsilon_{it} \quad \text{Equation 3.12}$$

The explanation of formulas in Equation 3.11 to 3.12 is as follows. Where i is the province, t is the year,$AGRTFP_{i,t}$ is the agricultural total factor productivity, $AGRTFP_{i,t-1}$ is the one-period lag of agricultural total factor productivity, $IN_{i,t}$ is the agricultural insurance, $CG_{i,t}$ is the country governance, $MH_{i,t}$ is the moral hazard, $X_{k,i,t}$ are the data matrix of a series of control variables including the agricultural structure, disaster impact, rural human capital, urbanization rate, the power level, pei capita disposable income of rural residents, β_0 is the constant term, β_1, β_2 and β_3 are parameters to be estimated;, β_k is the column vector of control variables, where the k th row element is the coefficient of the k control variable, and ε_{it} is the disturbance term.

3.7 Threshold Approaches for Analyzing the Impact of Agricultural Insurance on Agricultural Total Factor Productivity

3.7.1 Model Specification

Threshold Model is a type of statistical or econometric model used to describe and predict the sudden change in the current system or individual behavior near a critical point (threshold value). The core idea is that when a key variable (referred to as the "threshold variable") exceeds or falls below a certain threshold, the behavior or relationship of the system will undergo a structural change. Hansen (1999) proposed the panel threshold regression model, which solved the problem of estimating and inferring the threshold value in cross-sectional or panel data. Caner and Hansen (2004) addressed the endogeneity issue in the threshold model. Gonzalez et al. (2017) introduced the panel smooth transition

regression model. This new model is intended for characterizing heterogeneous panels, allowing the regression coefficients to vary both across individuals and over time.

Li and Li (2025) found that agricultural insurance generally played a positive role in increasing farmers' income; constrained by farmers' income levels, agricultural insurance had a distinct "threshold" characteristic for its impact on farmers' agricultural income: when farmers' income level exceeded a certain threshold, agricultural insurance would significantly increase farmers' income; if farmers' income was not high, the impact of agricultural insurance on farmers' income was not obvious. Zhou et al. (2023) empirical results showed that the impact of agricultural insurance on rural revitalization had a double threshold effect. Bhuiyan et al. (2022) found that the threshold model test found that in different insurance density ranges and insurance compensation areas, the effect of agricultural insurance on farmers' income is significantly different. Zhu et al. (2024) found that the impact of agricultural insurance on agricultural carbon productivity had a single threshold effect based on the proportion of agricultural output value. When the proportion of agricultural output value exceeded the threshold value, agricultural insurance would have a significant promoting effect on agricultural carbon productivity.

In conclusion, there may be a non-linear relationship between agricultural insurance and agricultural total factor productivity. So, referring to Li and Li (2025) and Bhuiyan et al. (2022), this section uses agricultural insurance as the threshold variable to study the impact of agricultural insurance on the total factor productivity of agriculture in China provinces. The model is set as follows:

$$\begin{aligned} AGRTFP_{i,t} = {} & \beta_0 + \beta_1 IN_{i,t} I(IN_{i,t} \le \gamma_1) + \beta_2 IN_{i,t} I(\gamma_1 < IN_{i,t} \le \gamma_2) \cdots + \\ & \beta_k IN_{i,t} I(\gamma_{k-1} < IN_{i,t} \le \gamma_k) + \beta_{k+1} IN_{i,t} I(IN_{i,t} > \gamma_k) + \\ & \boldsymbol{\beta X} + \varepsilon_{it} \end{aligned} \qquad \text{Equation 3.13}$$

The explanation of formulas in equation 3.13 is as follows. Where i is the province, t is the year, $AGRTFP_{i,t}$ is the agricultural total factor productivity, $IN_{i,t}$ is the agricultural insurance, $I(\cdot)$ is the conditional function, its value is 1 when the condition within the parentheses is satisfied, and 0 otherwise, X are the data matrix of a series of control variables including the agricultural structure, disaster impact, rural human capital, urbanization rate, the power level, pei capita disposable income of rural residents, β_0 is the constant term, β_1, β_2 , β_k and β_{k+1} are parameters to be estimated; β is the column vector of control variables, where the k is the number of threshold conditions, γ_k is the value of the k th threshold, and ε_{it} is the disturbance term.

3.7.2 Determination and Inference of Threshold Values

To examine potential nonlinear effects, this study employs a panel threshold regression model following Hansen (1999). A key issue in this framework is the estimation and statistical inference of the threshold value(s).

i. Determination of threshold value(s)

The threshold value(s) are determined using a grid search procedure. Specifically, the threshold variable is first sorted in ascending order, and candidate threshold values are selected from the interior of the sample, excluding extreme observations through a trimming rule (typically the lowest and highest 5% of the threshold variable). For each candidate value, the model is estimated by minimizing the sum of squared residuals. The estimated threshold value is defined as the value that yields the minimum residual sum of squares.

When the model allows for multiple thresholds, the grid search procedure is applied sequentially to identify additional threshold values, conditional on the previously estimated thresholds.

ii. Statistical significance of the threshold effect

Because the threshold parameter is not identified under the null hypothesis of no threshold effect, conventional asymptotic tests are invalid. Therefore, following Hansen (1999), this study adopts a bootstrap procedure to test the statistical significance of the threshold effect.

Specifically, the null hypothesis of no threshold effect is tested using a likelihood ratio (LR) statistic. The empirical distribution of the LR statistic is obtained through repeated bootstrap resampling, and the corresponding bootstrap p-values are calculated. If the bootstrap p-value is below conventional significance levels, the null hypothesis is rejected, indicating the presence of a statistically significant threshold effect.

In addition, confidence intervals for the estimated threshold value(s) are constructed based on the inverted likelihood ratio function, which provides statistical inference on the precision of threshold value(s).

3.8 Chapter Summary

This chapter uses data from 31 Chinese provinces and applies the DEA – Malmquist index to measure agricultural total factor productivity. Subsequently, a baseline regression model is established to study the impact of agricultural insurance on total factor productivity of agriculture in China province, and the robustness test method is designed.

Next, fixed effect models and GMM models are constructed to study the impact of agricultural insurance on total factor productivity of agriculture in China province. Then, the fixed effects and GMM models are extended to incorporate country governance and moral hazard as moderating variables to construct a robust model to study the impact of agricultural insurance on agricultural productivity in China provinces. Finally, with agricultural insurance as the threshold variable, a threshold model is constructed to further confirms the impact of agricultural insurance on total factor productivity of agriculture in China provinces.

CHAPTER 4

EMPIRICAL RESULTS AND DISCUSSION

4.1 Introduction

This chapter reports and discusses changes in agricultural total factor productivity (TFP) in China and its provinces and to estimate the determinants of provinces agricultural total factor productivity. Section 4.2 provides the results and analyzes of the agricultural total factor productivity of China and its provinces based on the DEA-Malmquist productivity index approach. Section 4.3, descriptive statistics for ananlysis of agricultural insurance impact on agricultural total factor productivity. Section 4.4, the impacts of agricultural insurance development on agricultural total factor productivity are analyzed using the baseline regression model. This is followed by a robustness test for the baseline analysis in section 4.5. The GMM analysis is extended, by introducing two moderating variables, namely country governance and moral hazard, to analyze the relationship between agricultural insurance development and agricultural TFP in China provinces in section 4.6. Finally, the Threshold Model further confirms the impact of agricultural insurance on the total factor productivity of agriculture in China provinces in section 4.7.

4.2 Results And Discussions of Agricultural Total Factor Productivity

This section measures the agricultural TFP of China's provinces from 2007 to 2023 using the DEA-Malmquist index method and analyzes the research results. The study finds that during the period from 2007 to 2023, China's total factor productivity growth mainly relied on technological progress (EC), while technical efficiency (EC) slightly

declined. These findings align with earlier research. For instance, Zhu (2022) and Zhang (2023) discovered that while technological efficiency gains have been minimal or even detrimental in certain provinces, technological change has been the primary driver of agricultural TFP growth in China. Similar to this, Zeng and Zhang (2022) found that border changes, not catching-up effects, are mostly responsible for the TFP rise in China's agriculture using a Malmquist index technique. Due to the different natural resources and economic foundations of each province in China, there are significant differences in agricultural total factor productivity among the provinces (Fan & Wang, 2025).

4.2.1 Results and Discussions on China's Agricultural TFP at the National Level

As shown in Table 4.1, the total factor productivity (TFP) of China's agriculture and its average annual growth rate from 2007 to 2023 was 6.7%, which is higher than the average annual growth rate of China's agricultural TFP from 2007 to 2019 as suggested by Zhu (2022), which was 4.66%. This indicates that China's agricultural productivity has continued to improve. Among them, the growth rate was the highest in 2019-2020 (13.4%), possibly due to the policy support and increased technological investment at the beginning of the pandemic; 2016-2017 was the only year with negative growth (-1.2%), possibly affected by extreme weather or agricultural restructuring (Li, 2024).

With an average annual technological change (TC) growth rate of 7.2% from 2007 to 2023, TC has been the main driver of agricultural TFP growth in China. As a result of the substantial influence of cutting-edge technologies including digital farming platforms, biotechnology, and agricultural mechanization, TC growth soared to 21.2% in 2019–2020.

These results are in line with Ye and Yang (2025), who highlighted how smart agriculture policy and mechanization subsidies propel technological developments in the industry.

The growth rate of TC in China from 2010 to 2019 calculated by Peng (2022) was 3.68%. Technological efficiency (TE) has almost stagnated (with an average annual growth rate of -0.2%), improving only in a few years (such as 2022-2023), indicating that there are still deficiencies in resource allocation and management optimization. The growth rate of TE calculated by Wang (2024) for China from 2003 to 2021 was 0.87%. This indicates that China's agricultural development shows a trend of continuous technological progress and a slight decline in technological efficiency. The total factor productivity of China's agriculture has maintained a relatively fast growth rate mainly relying on technological progress (Yang, 2023).

Table 4.1: China's Agricultural TFP Index and Its Decomposition from 2007 To 2023

Year	TFP Change (Malmquist Index)	Technical Progress (TC)	Technical Efficiency (EC)
2007-2008	1.073	1.048	1.024
2008-2009	1.035	1.033	1.002
2009-2010	1.088	1.112	0.990
2010-2011	1.085	1.122	0.968
2011-2012	1.059	1.049	1.015
2012-2013	1.061	1.052	1.013
2013-2014	1.007	1.023	0.984
2014-2015	1.020	1.043	0.978
2015-2016	1.078	1.100	0.980
2016-2017	0.988	1.002	0.987
2017-2018	1.055	1.049	1.020
2018-2019	1.097	1.109	0.989
2019-2020	1.134	1.212	0.938
2020-2021	1.084	1.088	0.997
2021-2022	1.086	1.066	1.017
2022-2023	1.119	1.047	1.064
Average Growth Rate (2007-2023)	**1.067**	**1.072**	**0.998**

Compared with existing studies, agricultural TFP is dominated by technological progress, consistent with the research of Wang (2024), Zhu (2022), and Lu (2023): The growth of agricultural TFP in China mainly relies on technological progress (such as the promotion of improved varieties and intelligent equipment), rather than efficiency improvement. This contrasts with the more balanced growth of TC and EC in developed countries (such as the United States) (Fuglie, 2018). Agricultural technical efficiency has stagnated. The average annual growth rate of agricultural technical efficiency in this study is -0.2%, which is consistent with the finding of Zhang and Lu (2022) that the small-scale farming model in China leads to diseconomies of scale.

Through comparative analysis, China should continue to maintain its technological advancement advantage and strengthen research and development in cutting-edge fields such as genetic breeding and smart agriculture; make up for the efficiency shortcomings by promoting land transfer and cultivating new types of business entities, and optimize the allocation of production factors (Zhang, 2025).

As shown in Figure 4.1, the two lines that represent the cumulative value of agricultural TFP and TC generally exhibit an upward trend, whereas the lines that represent the cumulative value of EC slightly decline. The direction and amplitude of change of TFP and TC are more constant, whereas EC slightly declines. The aforementioned conclusion is further supported by the fact that the development of agricultural technology is the primary driver behind China's agricultural TFP growth (Zong, 2024).

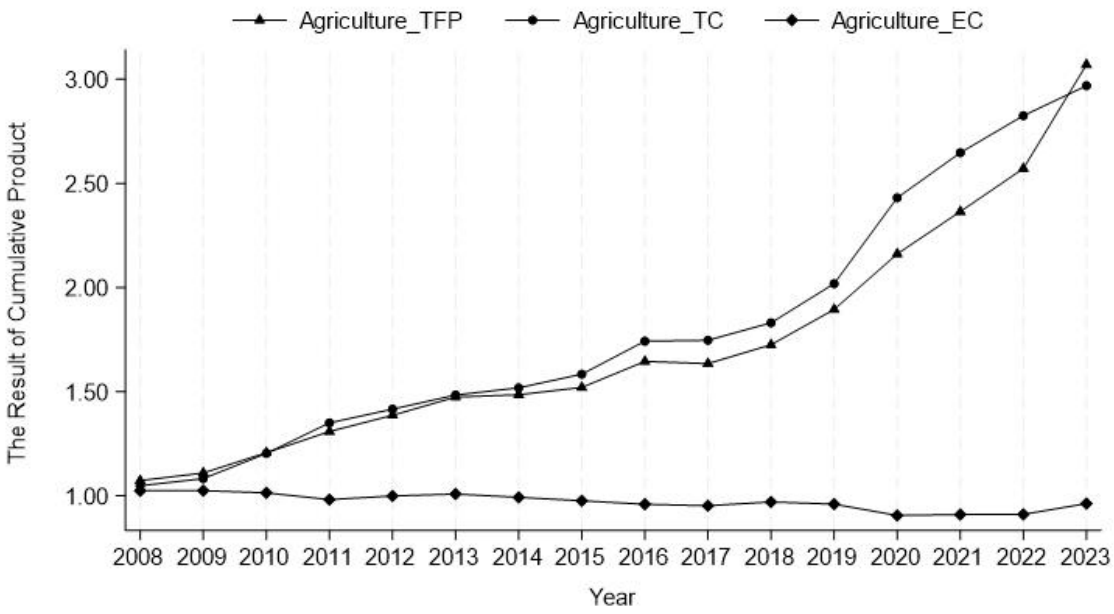

Figure 4.1: Cumulative Value and Decomposition of Total Agricultural TFP in China From 2008 to 2023

The research views of this study on China's agricultural TFP are basically consistent with those of other researchers. Han (2022) believes that the growth of China's agricultural TFP is influenced by the progress of agricultural technology and the improvement of agricultural technology efficiency, but the progress of agricultural technology is still the main driver of the growth of agricultural TFP. Zhou (2022) also found that the total factor productivity of agriculture in China showed a gradual growth trend, and the average annual growth rate of the country increased from 1.75% in 2007 to 4.84% in 2019. Gan (2022) also believes that China's agricultural total factor productivity increased gradually during 2011-2019.

4.2.2 Results And Discussions on Agricultural TFP at the Provinces Level

In order to better analyze the inter-provincial differences of agricultural TFP in China, the Malmquist index and its decomposition index of 31 provinces were averaged

from 2007 to 2023, so as to obtain the average annual index value of each province, and analyze the inter-provincial changes in agricultural TFP. As shown in Table 4.2 and Figure 4.2, the agricultural total factor productivity of different provinces in China is varied which indicates the average annual growth rate of agricultural TFP among different provinces is relatively different. From the specific value, the average annual growth rate of agricultural TFP in China's provinces from 2007 to 2023 is between 0.05% and 29.7%, among which the average annual growth rate of agricultural TFP in Xizang, Qinghai and Guizhou ranks the top three, and the average annual growth rate of agricultural TFP is 29.7%, 12.2% and 10.5% respectively. From the perspective of agricultural TC, the average annual growth rate of the three provinces is 12.9%, 9.2% and 8.8%, while from the perspective of agricultural TE, the average annual growth rate is 16.4%, 5.7% and 2.6%.

These results are consistent with earlier research by Zhou and Zhang (2023) and Li and Shen (2024), who observed that increased investment in agricultural infrastructure, ecological farming programs, and focused policy support have led to rapid TFP growth in Western China's underdeveloped provinces. Furthermore, Zhu (2022) highlighted that traditionally underperforming provinces have had a particularly large efficiency catch-up TE, which has reduced the regional productivity gap.

In addition, the average annual technical efficiency index of 20 provinces, including Inner Mongolia, Gansu, Jiangxi, Chongqing, Heilongjiang, Guangdong, Hebei, Anhui, Hunan, Hubei, Shandong, Jiangsu, Guangxi, Henan, Sichuan, Beijing, Xinjiang, Liaoning, Jilin and Shanghai, is less than 1, indicating that agricultural technical efficiency has declined in these provinces, the reason is that the urbanization rate in these provinces is high and there is a significant loss of labor force (Zong & Lu, 2024).and the growth of

agricultural total factor productivity is completely driven by agricultural technological progress, and the deterioration of agricultural technical efficiency will weaken the positive impact of some technological progress on agricultural total factor productivity (Lv, 2024).

Table 4.2: Agricultural TFP Index and Decomposition of Each Province from 2007 to 2023

Province	TFP Change (Malmquist Index)	Technical Progress (TC)	Technical Efficiency (EC)
Xizang	1.297	1.129	1.164
Qinghai	1.122	1.092	1.057
Guizhou	1.105	1.088	1.026
Zhejiang	1.102	1.102	1.000
Tianjin	1.095	1.076	1.019
Shanxi	1.086	1.071	1.016
Hainan	1.086	1.063	1.025
Ningxia	1.079	1.070	1.010
Fujian	1.068	1.063	1.005
Yunnan	1.064	1.061	1.002
Shanxi	1.063	1.063	1.000
Inner Mongolia	1.062	1.069	0.996
Gansu	1.060	1.066	0.994
Jiangxi	1.059	1.069	0.992
Chongqing	1.059	1.062	0.998
Heilongjiang	1.058	1.070	0.990
Guangdong	1.057	1.061	0.997
Hebei	1.056	1.074	0.984
Anhui	1.055	1.068	0.988
Hunan	1.055	1.066	0.989
Hubei	1.051	1.063	0.989
Shandong	1.050	1.071	0.982
Jiangsu	1.050	1.074	0.992
Guangxi	1.045	1.062	0.985
Henan	1.042	1.069	0.977
Sichuan	1.040	1.061	0.980
Beijing	1.032	1.076	0.960
Xinjiang	1.029	1.066	0.967
Liaoning	1.025	1.070	0.959
Jilin	1.014	1.069	0.949
Shanghai	1.005	1.072	0.942

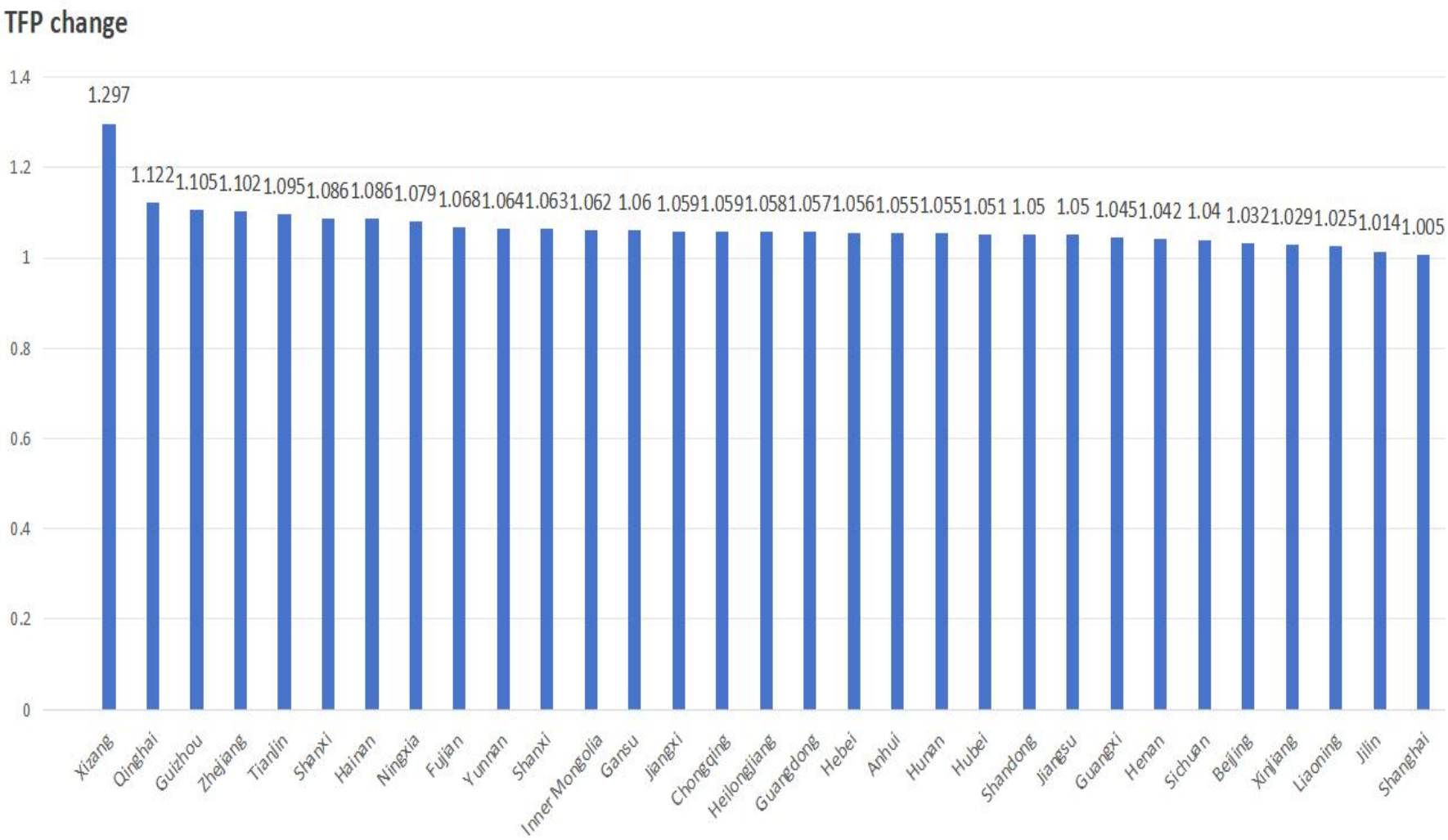

Figure 4.2: The Agricultural TFP Change by China Provinces (2008-2023)

He (2023) and Li and Shen (2024), who discovered significant regional variability in TFP growth driven by disparities in technology advancement, policy assistance, and resource endowments, support the idea that agricultural TFP varies greatly between Chinese provinces. Fan and Wang (2025) also ascribed these discrepancies to regional differences in infrastructure and innovative potential. Zhou (2022), however, challenges this view, claiming that inter-provincial variations in TFP growth have stayed mostly constant over time, pointing to a pattern of gradual convergence rather than divergence.

As shown in Figure 4.3, the TC values of various provinces in China range from 1.061 (Sichuang) to 1.129 (Xizang), indicating that agricultural technology in these provinces have made positive progress during this period. Because of its lower baseline level of agricultural modernization, more room for technological catch-up, and more robust central government policy support and technical assistance programs, Xizang had the greatest TC rating of 1.129 among them. These results are in line with those of Li and Niu (2025), who highlighted how the region's quick technological advancement can be attributed to a combination of targeted development initiatives and underdeveloped starting conditions. Zhou and Zhang (2023) and Wang and Fan (2024) came to similar results, pointing out that the “catch-up effect” is particularly noticeable in frontier and underdeveloped provinces like Xizang.

The TC values in coastal provinces such as Zhejiang (1.102), Tianjin (1.076), Beijing (1.076), Jiangsu (1.074), Shanghai (1.072), and Shandong (1.071) are relatively high. This can be attributed to their strong economic foundations, advanced infrastructure, and robust capabilities in technology introduction, absorption, and innovation. Guo et al. (2025) claim that these provinces gain from substantial R&D investment, developed

agricultural science and technology systems, and institutional settings that support growth driven by innovation. Liu and Yang (2023) and Zhang and Li (2024) made similar findings, emphasizing that agricultural technology is more advanced in economically developed areas with better access to innovation networks and capital resources.

In contrast, the TC values in several underdeveloped western provinces, including Gansu (1.066), Guangxi (1.062), Yunnan (1.061), and Sichuan (1.061), are relatively low. This reflects persistent limitations in economic development, infrastructure availability, and the effectiveness of agricultural technology promotion systems. Zheng and Wen (2024) claim that low investment in agricultural R&D, inadequate extension services, and a lack of adoption of contemporary technologies are the main causes of these regions' sluggish technical advancement. Fan and Wang (2025) and Li and Shen (2024) have pointed out that systemic obstacles to agricultural innovation in these regions include restricted access to institutional assistance, low human capital in farming communities, and poor connectivity.

In addition to the aforementioned reasons, as consumer demand for high-quality agricultural products increases, agricultural producers may be more inclined to adopt new technologies to improve yield and quality, driving technological progress. At the same time, the improvement of agricultural technology promotion systems and the enhancement of farmers' education levels have also played an important role in technological advancement (Wang & Yu, 2023).

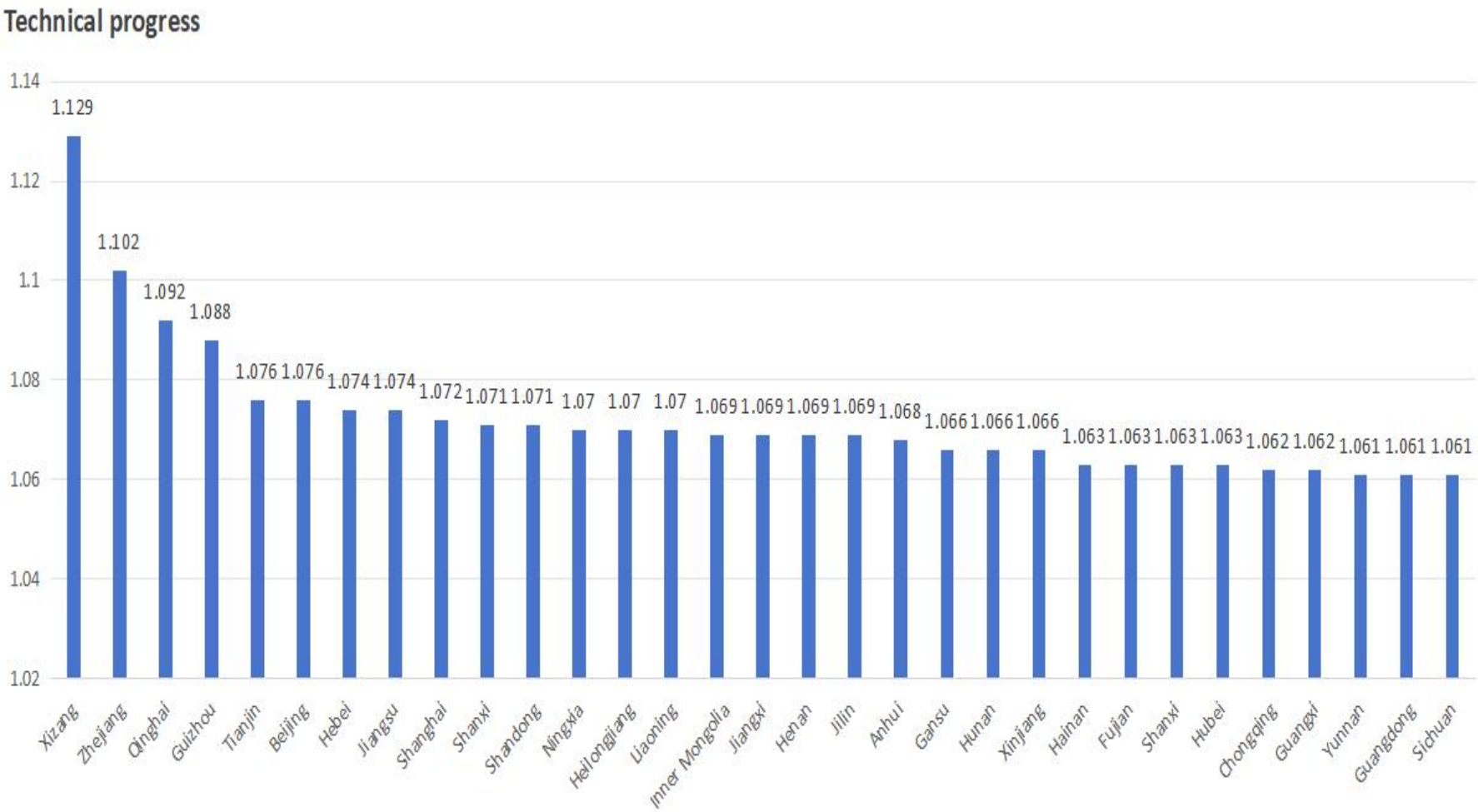

Figure 4.3: The Technical Progress (TC) by China Provinces (2008-2023)

As shown in Figure 4.4, the technical efficiency change (EC) values of various provinces in China range from 0.942 (Shanghai) to 1.164 (Xizang), indicating that there are large differences in agricultural technical efficiency among the provinces during this period. The top those provinces with highest EC value are Xizang, highest (1.164), followed by Qinghai (1.057), Guizhou (1.026). The reason for this is that the Chinese government has recently increased its policy support for these provinces and promoted the application of advanced technologies and equipment in agricultural production (Wang and Yu, 2023). These results are in line with those of Zheng and Wen (2024), who pointed out that public investment and agricultural modernization programs have been major drivers of technological efficiency advances in poor western regions. Liu and Zhang (2023) and Fan and Wang (2025) came to similar results.

The least EC values were recorded by coastal provinces such as Shanghai (0.942), Jilin (0.949), and Liaoning (0.959) are relatively low, possibly because agricultural production in these areas is already quite advanced, leaving limited room for further efficiency improvements (Qi et al., 2023). According to Chen and Hu (2024), developed provinces frequently encounter a “efficiency plateau,” when the marginal return on new investments aimed at increasing efficiency declines. This observation is consistent with their findings. Additionally, Zhou and Zhang (2023) contended that any efficiency gains in coastal locations may be impeded by institutional and structural saturation in agricultural production systems.

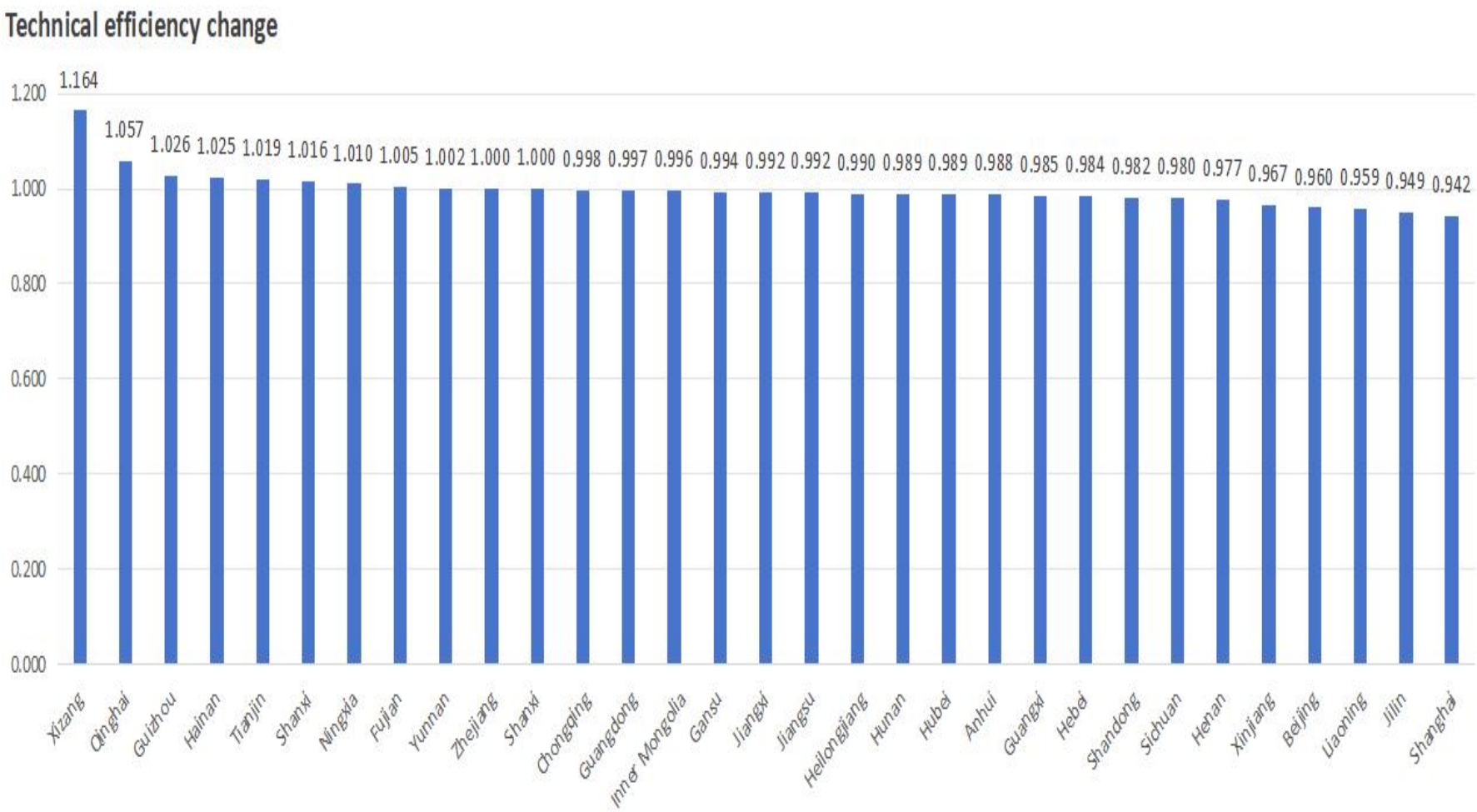

Figure 4.4: The Technical Efficiency (EC) by China Provinces (2008-2023)

In addition, the natural resource endowments of different regions such as land and water resources may affect agricultural technology efficiency, with resource-rich areas potentially achieving efficient production more easily (Fan & Wang, 2025). The promotion of efficient agricultural technologies and management methods also helps to improve production efficiency (Li, 2024).

4.3 Descriptive Statistics for the Analysis of Agricultural Insurance Impact on Agricultural TFP

As showed in Table 4.3, the dependent variable, agricultural total factor productivity (AGRTFP), has a mean value of 1.727 and a standard deviation of 1.008, suggesting substantial variation in productivity across provinces and years. The minimum value is 0.808, while the maximum reaches 17.904, indicating the presence of potential outliers or highly efficient regions.

The independent variable, agricultural insurance (IN), is measured by the logarithm of per capita agricultural premium income. It has a mean of 5.141 and a standard deviation of 1.516, with a wide range from -0.278 to 8.943, reflecting considerable heterogeneity in insurance coverage and investment levels across regions. The moderating variables include country governance (CG) and moral hazard (MH). Country governance has a mean of 0.354 and ranges from -0.005 to 0.808, while the moral hazard index has a relatively high mean of 3.493 and ranges from 0.758 to 7.508, indicating high variation across regions.

Other independent variables are also included. Rural income (log) has a mean of 9.306 with limited variation, suggesting relatively stable income levels. The power level

(log of electricity consumption) varies widely, ranging from -0.511 to 7.606, indicating significant differences in agricultural infrastructure. Urbanization rate and rural human capital (measured by years of schooling) also show regional disparities. Disaster impact and agricultural structure (grain crop ratio) exhibit moderate variation, which may influence agricultural output and efficiency.

Overall, the descriptive statistics show that the dataset captures diverse conditions across China's provinces, supporting robust empirical estimation.

Table 4.3: Descriptive Statistics for the Analysis of Agricultural Insurance Impact on Agricultural TFP

Variable Abbreviation	Variable Name	Unit	Mean	Standard Deviation	Min	Max
AGRTFP	Agricultural TFP	Index	1.727	1.008	0.808	17.904
IN	Agricultural insurance	Yuan/person (logarithm)	5.141	1.516	-0.278	8.943
CG	Country governance	Index	0.354	0.246	-0.005	0.808
MH	Moral hazard	Ten thousand tons	3.493	1.260	0.758	7.508
Income	Per capita disposable Income of rural residents	RMB Yuan (logarithm)	9.306	0.567	7.910	10.669
Power	The power level	Billion kilowatt-hours (logarithm)	4.695	1.490	-0.511	7.606
Urbanization	Urbanization rate	%	57.781	13.831	21.900	89.600
Rural Human Capital	Rural human capital	Year (logarithm)	7.683	0.856	3.819	10.324
Disaster	Disaster impact	%	0.075	0.072	0.000	0.376
Agrstr	Agricultural structure	%	0.651	0.139	0.353	0.971

4.4 Baseline Regression Results for Agricultural TFP Model

4.4.1 Result of Multicollinearity Test

Table 4.3 reports the variance inflation factors (VIFs) and tolerance values for all dependent variables included in the baseline regression model, which are used to assess the presence of multicollinearity. As a general rule, a VIF value exceeding 10 or a tolerance value below 0.1 indicates a potential multicollinearity problem.

Overall, the results show that the VIF values for all dependent variables are well below the conventional threshold of 10, and all tolerance values exceed 0.1, suggesting that multicollinearity is not a serious concern in the model and that the explanatory variables exhibit sufficient independence.

Specifically, the core dependent variable agricultural insurance (IN) has a VIF of 4.592 and a tolerance of 0.218, which fall within an acceptable range. This indicates that although agricultural insurance is correlated with some control variables, the degree of correlation is not strong enough to undermine the stability or statistical significance of the coefficient estimates. Country governance capacity indicator (CG) and the moral hazard variable (MH) display relatively low VIF values of 2.743 and 1.780, respectively, with tolerance values above 0.3, implying weak correlations with other regressors.

Among the control variables, per capita disposable income of rural residents (Income) exhibits a relatively higher VIF value of 9.579 and a tolerance of 0.104, approaching but not exceeding the commonly accepted critical values. This outcome is economically intuitive, as income levels are closely associated with urbanization, electricity consumption, and human capital. Nevertheless, since the VIF remains below 10

and the tolerance slightly exceeds 0.1, this variable does not generate severe multicollinearity and is therefore retained in the model to avoid omitted variable bias.

The remaining variables—including the power level (Power), urbanization rate (Urbanization), rural human capital (Rural Human Capital), disaster impact (Disaster), and agricultural structure (Agrstr)—all exhibit VIF values ranging from 1.108 to 4.146, with relatively high tolerance values. This indicates weak correlations among these variables and suggests that their inclusion does not compromise the reliability of the regression results.

In summary, the multicollinearity diagnostics confirm that multicollinearity does not pose a substantive problem in the baseline regression model. All dependent variables can be jointly included, and the estimated coefficients are considered stable and reliable.

Table 4.4: Result of multicollinearity test

Dependent Variable	**Multicollinearity test**	
	VIF	**Tolerance values**
IN	4.592	0.218
Income	9.579	0.104
Power	1.899	0.527
Urbanization	4.146	0.241
RuralHumanCapital	3.018	0.331
Disaster	1.465	0.682
Agrstr	1.108	0.903

Note: IN represents agricultural insurance, Income represents the per capita disposable income of rural residents, Power represents the power level, Urbanization represents the urbanization rate, Disaster represents disaster impact, and Agrstr represents the agricultural structure.

4.4.2 Baseline Regression Results for Agricultural TFP Model Using Fixed Effect and Random Effect Estimates

Table 4.5 reports the baseline regression results for agricultural TFP model in China provinces. This study conducted both the F test for fixed effects and the Hausman specification test to determine the appropriate panel data model. The results indicate that the F test for the fixed effects model is statistically significant ($F = 6.12$, $p < 0.01$), rejecting the null hypothesis that pooled OLS is adequate and confirming the presence of significant individual effects. In addition, the Hausman test statistic is highly significant ($\chi^2 = 59.24$, $p < 0.01$), leading to the rejection of the null hypothesis that the random effects estimator is consistent. These results jointly indicate that the unobserved individual effects are correlated with the explanatory variables, and therefore the fixed effects model is preferred over both pooled OLS and random effects models for the subsequent analysis. Therefore, the fixed effects is efficient and stable estimator for the static model analysis results are used as the final basis for interpretation (Wang & Ling, 2024). Therefore, the following discussion focuses primarily on the fixed effects estimates, while the pooled OLS and random effects results are presented for comparison to assess the consistency of the findings.

Under the fixed effects specification, agricultural insurance exhibits a positive and statistically significant impact on agricultural total factor productivity. This result suggests that, after controlling for time-invariant provincial heterogeneity and common time effects, the development of agricultural insurance contributes to productivity growth by reducing production risk, stabilizing farmers' income expectations, and encouraging more efficient allocation of production factors. Importantly, the positive coefficient of agricultural

insurance is also observed in the pooled OLS and random effects models, indicating that the estimated effect is robust across different model specifications, although the magnitude of the coefficient increases under fixed effects. This pattern implies that ignoring unobserved provincial characteristics may lead to an underestimation of the productivity-enhancing role of agricultural insurance.

Table 4.5: Baseline Regression Results of Pooled OLS, Random Effects and Fixed Effects Models

Dependent Variable	Pooled OLS	Random Effects	Fixed Effects
	(1) AGRTFP	(2) AGRTFP	(3) AGRTFP
IN	0.047	0.188***	0.229***
	(0.888)	(2.965)	(2.905)
Income	1.131***	0.843***	4.260***
	(6.210)	(4.121)	(4.210)
Power	-0.043	0.049	0.348***
	(-1.175)	(1.031)	(4.408)
Urbanization	-0.021***	-0.021***	-0.017
	(-3.796)	(-2.839)	(-0.738)
Rural Human Capital	-0.194***	-0.207**	0.309
	(-2.663)	(-2.217)	(1.626)
Disaster	0.350	0.062	0.087
	(0.527)	(0.092)	(0.133)
Agrstr	0.107	-0.097	1.153
	(0.364)	(-0.228)	(1.039)
Province Fixed Effect	No	No	Yes
Time Fixed Effect	No	No	Yes
_cons	-6.240***	-4.446***	-42.870***
	(-4.302)	(-2.797)	(-5.069)
Hausman Test			59.24***
F Test			6.12***
N	496	496	496
R^2	0.224	-	0.523

Note: T-statistics in brackets, *, **, *** indicates significant at the level of 10%, 5%, 1% respectively, IN represents agricultural insurance, Income represents the per capita disposable income of rural residents, Power represents the power level, Urbanization represents the urbanization rate, Disaster represents disaster impact, and Agrstr represents the agricultural structure.

4.4.3 The Results of Diagnostic Tests for Fixed Effect Model

4.4.3.1 The Results of Serial Correlation Test

Table 4.6 presents the results of the serial correlation test for the fixed effect model. The null hypothesis of no serial correlation is strongly rejected. Specifically, the t-statistic is 5.633 with 486 degrees of freedom, the F-statistic is 31.732 with degrees of freedom (1, 486), and the Chi-square statistic is 31.732 with one degree of freedom. All corresponding p-values are 0.0000, indicating statistical significance at the 1% level.

These results provide clear evidence of within-panel serial correlation in the error terms, implying that the disturbances for the same province are correlated over time. Such serial dependence is common in provincial panel data and does not bias the coefficient estimates of the fixed effects model. However, failing to account for serial correlation may lead to underestimated standard errors and overstated statistical significance.

Table 4.6: Result of serial correlation test

Test Statistic	Value	df	Probability
t-statistic	5.633116	486	0.0000
F-statistic	31.73200	(1, 486)	0.0000
Chi-square	31.73200	1	0.0000

To address the significant serial correlation in the disturbance terms of the fixed effects model, the model is re-estimated using heteroskedasticity-robust standard errors clustered. The corresponding estimation results are reported in Table 4.6 model 1.

As shown in the table 4.9 model 1, the adjusted R-squared is 0.393, indicating that the model explains approximately 39.3% of the variation in agricultural total factor productivity and exhibits a satisfactory goodness of fit. Moreover, the regression standard errors have been adjusted using heteroskedasticity-robust methods to ensure the reliability of statistical inference.

The regression results (Model1) show that the core independent variable, agricultural insurance has an estimated coefficient is statistically significant and positive, consistent with the theoretical expectation. This finding suggests that the development of agricultural insurance significantly promotes improvements in agricultural total factor productivity. Among the control variables, rural human capital has a coefficient significant positive. In contrast, the coefficient of agricultural structure is significant negative. In addition, per capita disposable income of rural residents, the power level, urbanization rate, disaster impact. (Income) do not reach conventional levels of statistical significance.

4.4.3.2 The Results of Cross-Sectional Dependence Test

Table 4.7 reports the results of the cross-sectional dependence test based on the Pesaran CD statistic. The test statistic is 27.20032, with a corresponding p-value of 0.0000, leading to a strong rejection of the null hypothesis of cross-sectional independence at the 1% significance level.

This result indicates the presence of significant cross-sectional dependence among provinces, suggesting that unobserved shocks or common factors—such as macroeconomic conditions, nationwide agricultural policies, climate variability, or technological spillovers—simultaneously affect agricultural total factor productivity across regions. Such

cross-sectional correlation is common in provincial panel data and, if ignored, may result in biased standard errors and misleading statistical inference.

Table 4.7: Result of cross-sectional dependence test

Test	Statistic	df	Probability
Pesaran CD	27.20032		0.0000

Given the existence of cross-sectional dependence, conventional fixed effects estimators with standard robust errors may be insufficient for valid inference. Therefore, this study using Driscoll–Kraay standard errors to adjust the model. The regression results of the revised model are presented in Table 4.6, Model 2.

From Table 4.9, it can be seen that this study adjusted the panel fixed effects model using the Driscoll-Kraay standard error to ensure the validity of the estimation results. The specific regression results (Model 2) are as follows: The coefficient of the core independent variable agricultural insurance on agricultural total factor productivity is 0.185, which is significantly positive at the 1% statistical level. Compared with the unadjusted model, the significance level has further increased. The positive promoting effect of agricultural insurance on agricultural total factor productivity is robust.

The coefficients of control variables such as the power level significantly positive. The coefficient of agricultural structure is significantly negative. However, the regression coefficients of variables such as per capita disposable income of rural residents, rural human capital, urbanization rate, and disaster impact have not reached the significant level. In summary, the regression model adjusted by Driscoll-Kraay effectively solved the cross-sectional correlation problem.

4.4.3.3 The Results of Heteroscedasticity Test

Table 4.8 presents the results of the heteroskedasticity test based on the Breusch–Pagan LM statistic. The test statistic is 2416.040 with 465 degrees of freedom, and the corresponding p-value is 0.0000. Therefore, the null hypothesis of homoskedasticity is strongly rejected at the 1% significance level.

This result provides clear evidence of heteroskedasticity in the disturbance terms of the panel regression model, indicating that the variance of the error terms is not constant across observations. Such heteroskedasticity is common in provincial panel data due to substantial differences in economic scale, agricultural production conditions, and institutional environments across regions.

Table 4.8: Result of heteroscedasticity test

Test	Statistic	df	Probability
Breusch-Pagan LM	2416.040	465	0.0000

To further address the heteroskedasticity detected in the model, this study re-estimates the effects of agricultural insurance and other explanatory variables on agricultural total factor productivity using the weighted least squares (WLS) estimator, which assigns observation-specific weights to mitigate heteroskedastic disturbances.

After conducting tests for serial correlation, cross-sectional dependence, and heteroskedasticity and applying appropriate robustness corrections, the adjusted regression results of the baseline model are taken as the final estimates for interpretation and discussion.

As shown in Table 4.9, Model 3 reports the adjusted regression results of the baseline model. Model 3 estimated using the weighted least squares (WLS) method. The coefficient of the core independent variable, agricultural insurance remains statistically significant positive. Compared with the baseline model, the magnitude of the coefficient declines slightly but retains both its positive sign and statistical significance. This indicates that the promoting effect of agricultural insurance on agricultural total factor productivity is robust and does not fundamentally change following the adjustment for heteroskedasticity.

Turning to the control variables, several results are economically intuitive and consistent with prior studies.

First, rural income shows a significantly positive effect on agricultural TFP in the model 3. Consistent with the estimation results of the fixed effect model. Higher rural income levels reflect stronger production capacity and improved access to capital, which facilitate investments in modern inputs, mechanization, and technology adoption, thereby enhancing production efficiency. The consistently positive coefficients across all model specifications further confirm the stabilizing and productivity-promoting role of income growth in rural areas.

Second, the coefficient of agricultural structure statistically significant negative, indicating that a higher concentration in traditional crop production may hinder improvements in agricultural total factor productivity. This result suggests that a rigid and less diversified planting structure constrains efficient factor allocation, limits technological upgrading, and reduces the potential productivity gains from structural transformation. In particular, policy-induced crop specialization and farmers' risk-averse behavior may lead

to a preference for low-risk but low-efficiency production patterns, thereby exerting a negative impact on agricultural TFP.

Third, the coefficient of the power level is statistically insignificant because this variable mainly reflects household electricity use rather than electricity directly applied in agricultural production, resulting in a weak direct link with agricultural total factor productivity.

Fourth, although the coefficient of urbanization is positive, it does not reach conventional levels of statistical significance. This indicates that urbanization may have a potential productivity-enhancing effect on agricultural total factor productivity, but the magnitude of this effect remains limited during the sample period. One possible explanation is that the positive effects of urbanization—such as technology diffusion and market integration—are offset by countervailing forces, including rural labor outflows and agricultural land fragmentation, resulting in a weak average effect.

Fifth, Rural human capital exhibits a negative but statistically insignificant coefficient in the model 3. This suggests that, rural human capital does not exert a robust direct effect on agricultural total factor productivity. The negative sign may reflect structural mismatches between human capital accumulation and the skill requirements of modern agricultural production in certain regions.

Finally, the coefficients of disaster impact is negative not statistically significant in the model 3. This result may be attributed to the increasing role of risk management instruments, including agricultural insurance and government support policies, which mitigate the adverse productivity effects of natural shocks over time.

Overall, after correcting for serial correlation, cross-sectional dependence, and heteroskedasticity, the results of Model 3 indicate that agricultural insurance has a

statistically significant and robust positive effect on agricultural total factor productivity. Increases in rural residents' income further reinforce this effect, while an under-optimized agricultural industrial structure significantly constrains productivity improvements. These findings provide strong empirical support for the core conclusion of this study that agricultural insurance promotes improvements in agricultural total factor productivity through effective risk management mechanisms.

Table 4.9: The regression results of correcting the fixed effect model

Dependent Variable	(1)	(2)	(3)
	Model 1	**Model 2**	**Model 3**
	AGRTFP	**AGRTFP**	**AGRTFP**
IN	0.185* (2.856)	0.185*** (4.279)	0.136*** (4.914)
Income	-0.218 (-0.518)	-0.218 (-0.793)	0.645*** (4.123)
Power	0.430 (1.431)	0.430* (2.054)	0.029 (0.721)
Urbanization	3.275 (1.183)	3.275 (1.625)	0.149 (0.658)
Rural Human Capital	0.416* (1.889)	0.416 (1.719)	-0.036 (0.910)
Disaster	0.194 (0.223)	0.194 (0.388)	-0.022 (0.327)
Agrstr	-2.177** (-2.140)	-2.177*** (-4.038)	-1.134*** (3.376)
Constant	-1.234 (-0.305)	-1.234 (-0.384)	-3.134*** (3.754)
N	496	496	496
R-squared	0.393	0.417	0.425

Note: T-statistics in brackets, *, **, *** indicates significant at the level of 10%, 5%, 1% respectively, IN represents agricultural insurance, Income represents the per capita disposable income of rural residents, Power represents the power level, Urbanization represents the urbanization rate, Disaster represents disaster impact, and Agrstr represents the agricultural structure.

4.4.4 Discussions on the Baseline Regression Results

After accounting for serial correlation, cross-sectional dependence, and heteroskedasticity through appropriate model corrections, Model 3 reported in Table 4.8 is adopted as the final and most reliable specification for assessing the effect of agricultural insurance on agricultural total factor productivity. Focusing on the model 3 estimates reported in column (4) of Table 4.8, agricultural insurance exhibits a statistically significant and positive effect on agricultural TFP at the 1% level. This finding suggests that the development of agricultural insurance plays an important role in enhancing agricultural productivity.

Several mechanisms may explain this positive relationship. First, agricultural insurance facilitates risk dispersion and transfer, which reduces farmers' perceived production risks and alleviates their concerns about potential losses associated with adopting new technologies. By lowering risk aversion, insurance encourages the diffusion and application of agricultural technologies, thereby improving total factor productivity (Hazell et al., 2010). Second, agricultural insurance provides income protection and stabilizes farmers' output expectations, increasing their willingness to expand production scale and adopt productivity-enhancing inputs (Carter et al., 2014). Third, agricultural insurance can function as a form of implicit collateral, easing farmers' access to credit by mitigating lenders' concerns about default risk. This mechanism relaxes financial constraints, increases investment in agricultural machinery and equipment, and ultimately contributes to productivity growth (Carter et al., 2016).

Regarding the control variables, the results of Model 3 are broadly consistent with the existing literature on agricultural total factor productivity. The significantly positive

effect of rural income corroborates prior evidence that income growth enhances farmers' investment capacity, facilitates the adoption of modern inputs and technologies, and thereby promotes productivity growth (Yu & Zhou, 2020; Bhuiyan et al., 2022; Wen et al., 2023). In contrast, the significantly negative coefficient of agricultural planting structure supports recent findings that excessive concentration in traditional crops constrains efficient factor reallocation and limits technological upgrading, resulting in lower productivity gains (Feng et al., 2019; Lu, 2023; Yu & Huang, 2022). The insignificant effects of rural electricity consumption, urbanization, and rural human capital are also consistent with mixed evidence in the literature, suggesting that household-level electricity use weakly reflects productive agricultural inputs (Zhou, 2022), that the productivity-enhancing spillovers of urbanization may be offset by labor outflows and land fragmentation (Fan et al., 2020; Yu & Huang, 2022), and that skill mismatches limit the direct contribution of human capital to agricultural productivity (Feng et al., 2019; Lu, 2023). Moreover, the weak effect of natural disasters aligns with recent studies emphasizing the mitigating role of agricultural insurance and government support policies in cushioning productivity losses from shocks (Hazell et al., 2010; Wen et al., 2023).

The positive effect of agricultural insurance on agricultural TFP identified in this study is broadly consistent with existing empirical evidence, while also offering several important extensions. Previous studies have shown that agricultural insurance enhances productivity by improving risk management and economic security (Xu & Liao, 2014; Goodwin & Smith, 2013), increasing production inputs and outputs (Barreiro & Lipper, 2017; Gebresilassie & Barrett, 2019), encouraging the adoption of new technologies (Carter & Jensen, 2018), and stimulating production incentives and investment (Kumar & Singh, 2020). By confirming a positive insurance–TFP relationship using provincial panel

data from China, this study reinforces the generalizability of these findings in a large developing economy with substantial regional heterogeneity.

More importantly, this study contributes to the literature in three key ways. First, it provides robust evidence on the productivity-enhancing role of agricultural insurance, Second, by employing total factor productivity rather than partial productivity measures or output indicators, this paper captures efficiency gains arising from both technological progress and improved factor allocation, complementing recent studies on green and aggregate productivity (Zhu, 2022; He, 2024). Third, the analysis clarifies the role of control variables by disentangling within-province effects from cross-sectional differences, helping to reconcile mixed findings in the existing literature. Together, these contributions offer a more nuanced understanding of how agricultural insurance influences agricultural productivity.

4.5 Robustness Test Results

To verify the robustness of the empirical results in Table 4.8, Based on the fixed effects model, we used four methods for robustness tests as depicted in Table 4.9.

i. Province-clustered Standard Error

This study employs robust standard errors clustered at the province level to conduct robustness checks. The results are shown in the second column of Table 4.10. Agricultural insurance is significantly positively correlated with agricultural TFP at the 5% level, consistent with the model 3 estimation results, confirming the positive correlation between agricultural insurance and agricultural total factor productivity in various provinces of China. The electricity consumption of rural residents is positively correlated with

agricultural TFP at the 10% level, while it is insignificantly in the model 3. The urbanization rate, the education level of rural residents and the impact of disasters are all not significant, consistent with the results of the model 3. The per capita disposable income of rural residents and agricultural structure not significant, which is inconsistent with the estimation results of Model 3.

ii. Replace Independent Variables

In Table 4.9, this study used per capita premium as an independent variable to measure the development level of regional agricultural insurance from the perspective of income. Next, this section replaced the independent variable with the loss rate of agricultural insurance to measure the development level of agricultural insurance from the perspective of expenditure. The results are shown in the third column of Table 4.10. The loss ratio is significantly positive at the 5% level, consistent with the estimated results of the agricultural insurance development level in the model 3, confirming the positive correlation between agricultural insurance and agricultural TFP in various provinces of China. The results show the power, rural human capital and urbanization rate are significant positive, while not significant in the model 3. Per capita disposable income of rural residents and agricultural structure are not significant, which is inconsistent with the estimation results of Model 3. The insignificant impact results of the disaster are consistent with the estimated results of Model 3.

iii. Replace Dependent Variables

In Table 4.9, this study calculate the multiplicative of the agricultural productivity index as agricultural total factor productivity; to represent the efficiency changes brought about by technological advancement, this study also utilize the multiplicative form of the

technical efficiency index (EC) in place of agricultural TFP. The research has generally endorsed the use of technological efficiency as a stand-in for total factor productivity (TFP), particularly in studies that use the Malmquist index or DEA methodologies to break down productivity increases (Coelli et al., 2005; Zhang & Liu, 2020). As shown in the fourth column of Table 4.10, agricultural insurance is significantly positive at the 1% level, consistent with the estimated results of agricultural insurance development levels in the model 3, confirming the positive correlation between agricultural insurance and agricultural TFP in various provinces of China. In addition, the results show a significant positive of per capita disposable income of rural residents, while the impact of disasters not significant, consistent with the model 3 estimates. The urbanisation rate, the power level and the rural human capita are significantly positively correlated, while the results are not significant in the model 3. The agricultural structure result was not significant, but it was significantly negative in Model 3.

iv. Remove Suspicious Samples

Considering the impact of epidemic factors, the production, transportation and sales of most agricultural products slowing down and might stopped during the epidemic period, which greatly interfered with agricultural productivity. Secondly, to ensure the continuity of sample time, we excluded samples from 2020 and later. The results, as shown in the fifth column of Table 4.9, indicate that agricultural insurance is significantly positive at the 1% level, consistent with the estimated results of agricultural insurance development levels in the model 3, confirming the positive correlation between agricultural insurance and agricultural TFP across Chinese provinces. Next, the research results show that the agricultural structure has a significant negative correlation, while the power level, rural human capital, and disaster impact do not show significant correlations. This is consistent

with the estimation results of Model 3. The per capita disposable income of rural residents has a significant negative correlation, and the urbanization rate has a significant positive correlation, which is also inconsistent with the estimation results of Model 3.

Through the regression results of the above four robustness tests conducted, it can be seen that there is no high contingency problem in the conclusion of baseline regression static model in Table 4.9, and the robustness test in this study passes.

Table 4.10: Robustness Test Results

Variable	Province-clustered standard error	Alternate independent variable	Replace the dependent variable	Reduce time (exclude year 2020-2023)
	i	ii	iii	iv
	AGRTFP	AGRTFP	AGREC	AGRTFP
IN	0.229**		0.094***	0.107***
	(2.150)		(4.938)	(5.128)
LossRatio		0.265*		
		(1.938)		
Income	4.260	0.437	0.825***	-0.604**
	(1.391)	(1.371)	(3.387)	(-2.162)
Power	0.348*	0.419***	0.072***	0.017
	(1.833)	(4.786)	(3.474)	(0.315)
Urbanization	-0.017	0.041*	0.011**	0.048***
	(-0.383)	(1.922)	(2.006)	(6.675)
Rural Human Capital	0.309	0.556***	0.104**	0.069
	(1.478)	(2.950)	(2.266)	(1.245)
Disaster	0.087	-0.300	-0.185	-0.244
	(0.125)	(-0.432)	(-1.172)	(-1.474)
Agrstr	1.153	0.256	-0.393	-1.693***
	(0.581)	(0.226)	(-1.471)	(-5.305)
Province Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
_cons	-42.870	-11.300***	-8.711***	4.326*
	(-1.493)	(-5.636)	(-4.277)	(1.902)
N	496	496	496	372
R2	0.523	0.386	0.604	0.836

Note: T-statistics in brackets, *, **, *** indicates significant at the level of 10%, 5%, 1% respectively, IN represents agricultural insurance, LossRatio represents agricultural lossratio, Income represents the per capita

disposable income of rural residents, Power represents the power level, Urbanization represents the urbanization rate, Disaster represents disaster impact, and Agrstr represents the agricultural structure.

4.6 Moderating Effects Result of Country Governance and Moral Hazard Based on Fixed Effect Model and GMM Model

4.6.1 Regression Results of Fixed Effect of the Relationship Between Agricultural Insurance and Agriculture TFP with Country Governance and Moral Hazard as the Moderators

In this analysis, the baseline model is extended by incorporating between country governance and moral hazard as moderating variables. The model to examine how these moderators influence the relationship between agricultural insurance and agricultural total factor productivity (TFP). The regression results of the moderators' impact on the fixed effect model are shown in Table 4.11. The second column reports the test results of the moderating effect of country governance on the relationship between agricultural insurance and agricultural TFP.

The fact that agricultural insurance has a considerably positive coefficient suggests that it has a beneficial effect on agriculture's total factor productivity. This result is consistent with the study's Hypothesis H1, which postulates that the growth of agricultural insurance helps to raise agricultural TFP. This finding is in line with earlier research by Chen (2016), Li (2018), Gan (2022), and He (2024), which discovered that agricultural insurance can increase the effectiveness of resource allocation and encourage farmers to embrace contemporary agricultural technologies.

Additionally, the coefficient of the interaction term between agricultural insurance and country governance (IN×CG) is highly positive, indicating that the favorable impact of agricultural insurance on agricultural TFP is amplified by improved national governance capacity. This bolsters the study's second hypothesis, which holds that effective national governance encourages the growth of agricultural insurance and, in turn, raises agricultural production. This result is consistent with global research by Gani (2012), Cahan et al. (2016), and Ilhan (2022), who highlighted the moderating effect of government efficacy in enhancing the efficiency of financial instruments in the agriculture sector.

The results of income, disaster and agricultural structure were not significant. The coefficients of Power, Urbanization and Rural Human Capital are positive and significant, indicating that the increase of rural residents' electricity consumption, the increase of urbanization rate and the increase of rural residents' years of education can promote the increase of agricultural TFP. This study holds that improving the level of national governance is conducive to the development of agricultural insurance and the improvement of agricultural productivity, which is consistent with Vassilis' (2023) view. Vassilis (2023) believes that improving the quality of country governance can provide total factor productivity in transition economies such as Vietnam.

The third column reports the test results on the moderating effect of moral hazard. The coefficient of agricultural insurance remains significantly positive, indicating that agricultural insurance continues to have a significant positive effect on agricultural total factor productivity (TFP). This finding supports Hypothesis H1 of this paper, which states that the development of agricultural insurance contributes to the improvement of agricultural TFP, consistent with studies by Chen (2016), Li (2018), and Gan (2022).

Table 4.11: Fixed Effects Results of the Moderating Effects of Country Governance and Moral Hazard

Variable	Country Governance	Moral Hazard
	(1)	(2)
	AGRTFP	AGRTFP
IN	0.148*	0.458***
	(1.719)	(4.250)
CG	-3.813***	
	(-2.972)	
MH		0.313*
		(1.723)
IN×CG	0.413**	
	(2.319)	
IN×MH		-0.078***
		(-3.524)
Income	0.297	3.304***
	(0.633)	(3.202)
Power	0.433***	0.354***
	(5.007)	(4.163)
Urbanization	0.050**	-0.023
	(1.988)	(-1.006)
Rural Human Capital	0.455**	0.291
	(2.354)	(1.544)
Disaster	0.115	0.034
	(0.173)	(0.053)
Agrstr	0.497	0.160
	(0.441)	(0.124)
Province Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
Hausman Test	119.44	34.91
F Test	23.80	29.67
_cons	-10.018***	-33.724***
	(-3.003)	(-3.869)
N	496	496
R^2	0.493	0.538

Note:T-statistics in brackets, *, **, *** indicates significant at the level of 10%, 5%, 1% respectively, IN represents agricultural insurance, CG represents country governance, MH represents moral hazard, IN×CG represents agricultural insurance and country governance interaction, IN × MH represents agricultural insurance and moral hazard interaction,Income represents the per capita disposable income of rural residents, Power represents the power level, Urbanization represents the urbanization rate, Disaster represents disaster impact, and Agrstr represents the agricultural structure.

Moreover, the coefficient of the interaction term between agricultural insurance and moral hazard (IN×MH) is significantly negative, suggesting that an increase in moral hazard weakens the positive effect of agricultural insurance on TFP. This provides strong evidence for Hypothesis H3, which posits that moral hazard can undermine the role of agricultural insurance in promoting agricultural productivity. This result is aligned with previous findings in both domestic and international research (Qiao & Cai, 2021; Liu et al., 2023; Coble et al., 1997; Just et al., 1999), which emphasize that the presence of moral hazard may lead to distorted behavioral incentives, such as reduced input effort or overreliance on compensation mechanisms, thus dampening the productivity-enhancing effect of insurance.

According to the empirical findings, there is no statistically significant relationship between agricultural TFP and the variables of urbanization rate, rural human capital, disaster, and agricultural planting structure. On the other hand, rural power consumption and rural disposable income have significantly positive coefficients, suggesting that raising household income and rural infrastructure both boost agricultural output. These results are in line with earlier research that emphasizes the contribution of rural infrastructure and income growth to increasing agricultural output, including Zhao and Li (2020), Zhang and Li (2022), and Fan and Chan-Kang (2004).

The Hausman test values for the fixed effects results of the moderating effects of country governance and moral hazard are 119.44 and 34.91, respectively, both of which are greater than the critical value, rejecting the null hypothesis and proving that the fixed effects model is more effective. The F test values are 23.8 and 29.67, respectively, both of which are greater than the critical value, rejecting the null hypothesis and proving that the

fixed effects model is superior. In summary, the moderating effects model of country governance and moral hazard passed the Hausman test and F test, demonstrating that the estimation results using the fixed effects model are superior.

4.6.2 Regression Results of GMM on the Relationship Between Agricultural Insurance and Agriculture TFP with Country Governance and Moral Hazard as the Moderators

The development of agricultural insurance can enhance agricultural TFP, and regions with higher agricultural TFP may be more inclined to purchase agricultural insurance. There may be a bidirectional causal relationship between agricultural insurance and agricultural TFP, leading to endogeneity issues (Wang, 2024). To further ensure robustness of the result in this study, two step system GMM model for regression analysis is constructed to address the endogeneity issue.

Based on the second column of the system GMM regression results in Table 4.12, The coefficient of the lagged agricultural total factor productivity is significantly positive at the 1% level, indicating that agricultural TFP exhibits strong path dependence and persistence over time. This also supports the validity and dynamic structure of the system GMM estimation applied in this analysis. Furthermore, the coefficient of agricultural insurance is significantly positive at the 1% level, suggesting that the development of agricultural insurance significantly enhances agricultural TFP. This finding is consistent with the fixed-effects estimation in the baseline regression results and provides further evidence in support of Hypothesis H1 that the development of agricultural insurance contributes to the improvement of agricultural total factor productivity. The disposable

income of rural residents and the impact of disasters are significantly negatively correlated with total factor productivity in agriculture at the 1% level, indicating that the disposable income of rural residents and the impact of disasters have a negative effect on total factor productivity in agriculture.

Table 4.12: Regression Results of the Moderating Effects of Country Governance and Moral Hazard (System GMM Model)

Variable	GMM (No Moderating Variable)	Country Governance	Moral Hazard
	Model 1	Model 2	Model 3
	AGRTFP	AGRTFP	AGRTFP
L.AGRTFP	1.169*** (100.760)	0.854* (1.708)	1.204*** (29.916)
IN	0.107*** (7.539)	-1.207 (-1.591)	0.332*** (4.524)
CG		-7.524** (-2.315)	
MH			0.644*** (5.939)
IN×CG		1.303** (2.683)	
IN×MH			-0.120*** (-5.396)
Income	-0.414*** (-7.021)	5.348** (2.508)	0.445*** (8.991)
Power	0.001 (0.065)	-0.862** (-2.100)	-0.176*** (-6.138)
Urbanization	0.005 (1.024)	-0.145*** (-2.878)	-0.005** (-2.130)
Rural Human Capital	0.035 (1.479)	-0.409 (-0.654)	-0.028 (-0.791)
Disaster	-0.840*** (-6.042)	5.650 (1.030)	0.445 (1.305)
Agrstr	-0.110 (-0.596)	4.786 (1.301)	-0.077 (-0.699)
_cons	2.756*** (5.914)	-31.114* (-1.867)	-4.838*** (-7.238)
AR(1)	0.003	0.011	0.034
AR(2)	0.889	0.842	0.900
Hansen	0.913	0.498	0.998
N	465	465	465

Note: T-statistics in brackets, *, **, *** indicates significant at the level of 10%, 5%, 1% respectively, IN represents agricultural insurance, CG represents country governance, MH represents moral hazard, IN×CG represents agricultural insurance and country governance interaction, IN × MH represents agricultural insurance and moral hazard interaction,Income represents the per capita disposable income of rural residents, Power represents the power level, Urbanization represents the urbanization rate, Disaster represents disaster impact, and Agrstr represents the agricultural structure.

The P-value of the Hansen test is greater than 0.1, indicating that the instrumental variables used in the model are valid. Additionally, the AR(1) value is less than 0.1 and the AR(2) value is greater than 0.1, indicating that the model setting is reasonable.

Next, the regression results of the GMM model with the moderating variable are also shown in Table 4.12 via the third column, with the moderating effect of country governance using the interaction term between agricultural insurance and country governance (IN×CG). From the regression results in the third column of Table 4.12, it can be seen that the interaction coefficient between agricultural insurance and country governance is positive and highly significant. The P-values of the AR(2) and Hansen tests are greater than 0.1, the P-values of the AR(1) less than 0.1, indicating that the model setting is reasonable.

The results confirm that country governance positively moderates the relationship between agricultural insurance and the total factor productivity of agriculture. An improvement in the level of national governance further enhances the effectiveness of agricultural insurance in promoting agricultural productivity, thus supporting Hypothesis H2 of the improvement of country governance levels helps agricultural insurance promote the enhancement of total factor productivity in agriculture. This finding is consistent with the study by Vassilis (2023), who emphasized the role of institutional quality in enhancing

policy outcomes in agriculture. Other research has also reached similar conclusions. For example, Cahan et al. (2016) and Gani (2012) emphasized that improved governance increases the effectiveness of public programs and financial instruments, especially in the agricultural sector. According to Li and Zhang (2020), government efficacy and institutional quality are crucial for the successful execution of rural development initiatives, such as crop insurance programs, in China.

Besides that, the regression results indicate a significant positive correlation between the disposable income of rural residents and agricultural TFP, implying that rising rural income levels contribute to productivity improvement. This is in line with the conclusions of Huang and Gao (2020) and Fan et al. (2008), who highlighted how income growth propels agricultural modernization and rural investment.

In contrast, the urbanization rate shows a significant negative correlation with agricultural TFP, suggesting that higher levels of urbanization may divert labor and resources away from agriculture, thereby restraining productivity growth. This aligns with the conclusions of Zhang and Zhang (2021), who found that excessive urban expansion could lead to a hollowing-out of rural labor forces.

Moreover, the coefficient of agricultural insurance is not statistically significant, in contrast to other variables such as rural electricity consumption, educational attainment, natural disaster impact, and agricultural planting structure, all of which show no consistent significance across models. Similar inconclusive findings on these variables' influence on TFP were also reported by Wang et al. (2022) and Jin (2023), suggesting possible heterogeneity across regions or estimation methods.

Finally, the fourth column of Table 4.12 presents the regression results incorporating moral hazard as the moderating variable. The interaction term between agricultural insurance and moral hazard (IN×MH) is negative and statistically significant, indicating that moral hazard significantly weakens the positive impact of agricultural insurance on total factor productivity in agriculture. This result supports Hypothesis H3, which posits that moral hazard inhibits the effectiveness of agricultural insurance in enhancing agricultural productivity. The P-values of the AR(2) and Hansen tests are both above 0.1, while the AR(1) less than 0.1, confirming the validity and robustness of the model specification in the dynamic system GMM framework. These findings are in line with those of Liu (2021), and also echo the conclusions of Smith and Goodwin (2013), who argue that moral hazard is a key limitation in the effective operation of agricultural insurance systems, especially in developing economies.

The development of agricultural insurance helps to increase total factor productivity in agriculture, as evidenced by the estimated coefficient of agricultural insurance, which is significantly positive. Recent research by Zhu et al. (2022) and He and Wang (2024) supports this, confirming that agricultural insurance increases productivity by mitigating risk and providing incentives for the adoption of new technologies.

Additionally, the coefficient of disposable income for rural inhabitants is likewise strongly positive, indicating that greater income levels among rural populations can encourage innovation and investment in agricultural inputs, which will increase TFP (Fan & Zhang, 2021; Gao et al., 2023).

The urbanization rate and the power consumption of rural inhabitants, on the other hand, have large negative coefficients. This suggests that rapid urbanization and greater

energy use may be the result of labor outflows or structural inefficiencies, which would ultimately stifle productivity growth. This is consistent with the results of Liu (2022) and Chen et al. (2023).

The statistically negligible coefficients of other variables, such as disaster, agricultural planting structure, and rural residents' educational attainment, reflect the inconclusive or regionally varied findings in Jin (2023) and Wang et al. (2022).

Through the analysis of the moderating effects of the above two models, we find that the results in Table 4.5 (using fixed effects model) and Table 4.6 (using GMM model) are consistent, and the improvement of country governance can promote agricultural insurance to have a positive impact on agricultural TFP, which confirms the establishment of our H2, country governance affect agricultural insurance development in influencing total factor productivity performance of agricultural in China provinces. The increase of moral hazard inhibited the influence of agricultural insurance on agricultural TFP, which confirmed the establishment of H3, moral hazard affects agricultural insurance development in influencing total factor productivity performance of agricultural in China provinces.

Examining pertinent literature on country governance, we discover that Vassilis's (2023) perspective closely reflects the results of this investigation. Vassilis highlights the institutional underpinnings necessary for long-term economic efficiency by showing how improvements in country governance can dramatically raise total factor productivity in transition economies like Vietnam. The complex relationship between country governance and economic success in several areas has also been studied by other academics. For example, Po (2016) examined how governance reforms impact state-owned banks'

performance after privatization and found that governance quality has a major impact on banking accountability and efficiency. Ben (2021) also discovered that country with more robust governance structures typically have higher returns on equity, highlighting the importance of institutional integrity in financial success. Kamarudin (2022) further confirmed the productivity-enhancing potential of transparent and participative governance in the financial industry by emphasizing that certain governance characteristics, particularly voice and accountability, have a favorable impact on bank productivity. In line with the theoretical framework and empirical findings of this study, these studies collectively imply that raising the quality of country governance has a typically favorable effect on institutional performance and productivity.

Moral hazard exists widely in insurance, especially in agricultural insurance. Subsequent investigations and studies by Coble et al. (1997), Esuola et al. (2007), Smith and Glauber (2012) also showed that after farmers purchased crop insurance, some farmers planted crops on poor land. At the same time, reduce the use of production inputs such as fertilizers, so as to obtain additional insurance payments; Tuo and Zhu (2007) believe that because the subject matter of agricultural insurance is living organisms, agricultural disaster losses are characterized by co-occurrence, correlation, etc., and the moral hazard is more serious than that of general property insurance and difficult to prevent. Liu (2021) believes that moral hazard has always been a difficult issue in the operation of agricultural insurance, and moral hazard hinders the development of agricultural insurance. Through the comparative analysis of the above studies, we find that moral hazard inhibits the development of agricultural insurance, which is consistent with the viewpoint of this study.

According to Table 4.12, when taken into account alone in Model (2) the country governance (CG), it exhibits a significantly negative coefficient. This suggests that current governance mechanisms may have an inhibitory effect on agricultural TFP, possibly as a result of institutional rigidity, inefficiency, or imperfect coordination (Acemoglu & Robinson, 2012; Yu & Wang, 2022). However, there is a strong positive interaction term (IN×CG) between agricultural insurance and country governance, suggesting that better governance can increase the efficiency of agricultural insurance in boosting output. This finding points to a synergistic effect: strong governance frameworks can improve agricultural insurance's implementation, supervision, and trust, strengthening its ability to boost agricultural output (Vassilis, 2023).

Moreover, when the level of country governance is higher—measured by indicators such as regulatory quality, voice and accountability, and government effectiveness—the positive productivity impact of agricultural insurance becomes more pronounced (Kamarudin et al., 2022). These findings are consistent with the institutional productivity literature, which posits that institutional quality acts as a moderator in shaping the returns of economic and agricultural policies (Po, 2016; Ben, 2021).

The relationship between moral hazard (MH) and agricultural insurance (IN), represented as IN×MH, is found to be considerably negative in Model (3). This suggests that the beneficial impact of agricultural insurance on agricultural total factor productivity (TFP) is considerably diminished by moral hazard. By distorting incentives, moral hazard leads to inefficient allocation of agricultural inputs and even adverse selection, which hinders productivity gains and lowers the effectiveness of insurance mechanisms (Coble and Barnett, 2013).

This adverse moderating effect might occur because, despite its intended goal of stabilizing farmers' incomes, agricultural insurance may unintentionally cause behavioral distortions like excessive input use or a decrease in risk management effort, particularly when insurance coverage is seen as a replacement for self-defense (Cai, 2016; Zhao et al., 2021). As a result, the incentive issues that crop insurance creates in the face of moral hazard compromise its intended productivity-enhancing function.

The severity of the moral hazard problem in China's agriculture insurance market is also reflected in the IN×MH interaction term's observed inhibitory effect. Farmers may engage in opportunistic practices, such as overreporting losses or changing input choices after enrolling in insurance, which can result in higher payouts and inefficient use of insurance funds, according to a number of empirical research (Wen et al., 2020; Zhang & Zhu, 2019). These inefficiencies reduce insurance's ability to foster long-term increases in agricultural productivity and diminish its developmental significance.

Therefore, even while agricultural insurance is crucial for maintaining agricultural output stability, its ability to effectively boost productivity depends heavily on how well moral hazard is managed. These inefficiencies may be lessened and the beneficial productivity impacts of insurance schemes restored with the support of regulatory initiatives targeted at enhancing claim verification, encouraging actuarially fair pricing, and using precision agriculture technologies for loss assessment.

To sum up, the improvement of country governance can help improve the management level of agricultural insurance, and then promote the development of agricultural insurance, so as to better play the role of agricultural insurance in promoting agricultural total factor productivity. The existence of moral hazard will make the

development of agricultural insurance difficult, not conducive to the development of agricultural insurance, and then weaken the role of agricultural insurance in promoting the development of agricultural total factor productivity.

4.7 Estimation Results of the Threshold Model of Agricultural Insurance on Agriculture Total Factor Productivity in China Provinces

4.7.1 Estimation Results of the Threshold Variable

The baseline regression and GMM models reported in Table 4.9 and Table 4.12 do not fully consider the differences in the impact of agricultural insurance on total factor productivity of agriculture at different stages of development. To address this issue, this study extends the analysis to threshold model. According to Wei and Wang (2025), they examined the threshold effect of the agricultural insurance development level on total factor productivity in agriculture by using agricultural insurance as the threshold variable and conducting a self-sampling test as shown in Table 4.13. According to Table 4.13, although the level of agricultural insurance development passed the single-threshold test at the 5% significance level, obtaining a critical value of 7.35, the double-threshold did not pass the significance test, indicating that the effect of agricultural insurance development level on total factor productivity in agriculture has a single-threshold characteristic.

As shown in Table 4.14, the threshold effect was tested to obtain the threshold estimate, which is 7.4925. Next, a confidence interval is constructed to verify the authenticity of the threshold estimate.

Table 4.13: Results of the Threshold Effect Test

Model	Number of Thresholds	F Statistic	P-value	10% Critical Value	5% Critical Value	1% Critical Value
Single-threshold model	First threshold	54.75	0.0340	39.6365	48.7441	88.8810
Double threshold model	First threshold	54.75	0.0320	37.2169	48.7079	72.6078
	Second threshold	-0.93	1.0000	31.7905	44.7521	100.1325

Table 4.14: The Value of the Threshold Variable Under the Single-Threshold Model

Model	Threshold Value	Lower Bound of the 95% Confidence Interval	Upper Bound of the 95% Confidence Interval
Single-threshold model	7.4925	7.4550	7.4948

Figure 4.5 shows the likelihood ratio function graph of the threshold values existing in agricultural insurance within the 95% confidence interval. Among them, the lowest point of the LR statistic corresponds to the actual threshold value. The dotted line represents the critical value of the likelihood ratio statistic at the 5% level, which is 7.35. Since the critical value of 7.35 is significantly greater than the likelihood ratio statistic corresponding to the threshold value, it can be concluded that the aforementioned threshold value is truly valid.

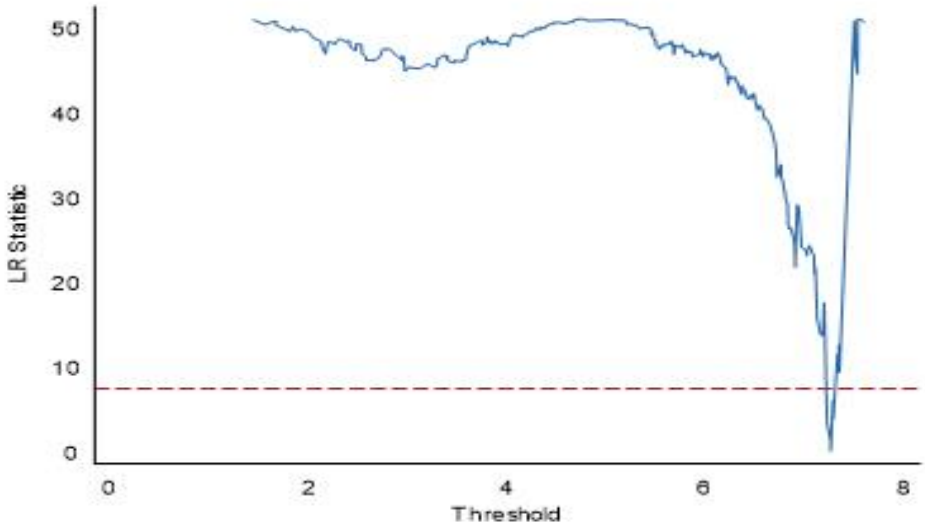

Figure 4.5: The LR Test Results for the Threshold Value

4.7.2 The Regression Results and Analysis of the Threshold Model of Agricultural Insurance on Agricultural Total Factor Productivity

Table 4.15 presents the regression results of the threshold model with agricultural insurance as the threshold variable. When the level of agricultural insurance is at a low level, it is significant at the 1% level, and its impact coefficient on agricultural total factor productivity is 0.255; when the level of agricultural insurance is at a high level, it is also significant at the 1% level, and its impact coefficient on agricultural total factor productivity is 0.477. Based on the above results, there is a non-linear impact relationship between agricultural insurance and agricultural total factor productivity. When the level of agricultural insurance reaches a certain threshold, the promoting effect of agricultural insurance on agricultural total factor productivity will further strengthen. It has been proved that hypothesis 4 is valid, the development of agricultural insurance has a threshold effect on the total factor productivity of agriculture in China provinces.

Table 4.15: Threshold Model Regression Results of Agricultural Insurance on Agricultural TFP

Variables	(1)
	AGRTFP
IN≤7.4925	0.255***
	(3.338)
IN>7.4925	0.477***
	(6.004)
Income	-1.367***
	(-4.151)
Power	0.481***
	(5.819)
Urbanization	0.107***
	(4.947)
Rural Human Capital	0.344**
	(2.028)
Disaster	0.226
	(0.362)
Agrstr	0.276
	(0.259)
_cons	1.796
	(0.860)
N	496
R^2	0.432

Note: T-statistics in brackets, *, **, *** indicates significant at the level of 10%, 5%, 1% respectively, IN represents agricultural insurance, Income represents the per capita disposable income of rural residents, Power represents the power level, Urbanization represents the urbanization rate, Disaster represents disaster impact, and Agrstr represents the agricultural structure.

When the level of agricultural insurance is low, the promoting effect of agricultural insurance on the total factor productivity of agriculture is relatively weak. This might be due to the insufficient insurance coverage, which restricts the adoption of new technologies or high-yield crops by farmers, thereby resulting in a relatively weak promoting effect on the total factor productivity of agriculture (Liu et al., 2025).

When the coverage rate of agricultural insurance reaches the threshold, the promoting effect of agricultural insurance on the total factor productivity of agriculture significantly increases. The possible reasons include: Firstly, agricultural insurance reduces the risks in agricultural production, motivating farmers to adopt high-input and high-return technologies. Secondly, as collateral, agricultural insurance alleviates farmers' credit constraints and promotes agricultural production investment. Thirdly, the high insurance level of agricultural insurance may be accompanied by agricultural large-scale operation, thereby enhancing agricultural production efficiency (Zhou et al., 2023).

The coefficient of rural residents' disposable income is significantly negative. The possible reason is that the increase in rural residents' disposable income leads to the loss of rural labor force, which in turn results in the decline of agricultural total factor productivity (Ye & Zhang, 2025). The coefficient of rural residents' electricity consumption is significantly positive. The reason is that in rural areas, a large number of electrical equipment such as electric seeders, sprinkler irrigation equipment, and electric harvesters are used in sowing, irrigation, harvesting, and field management. The use of these devices has improved agricultural production efficiency and also led to an increase in rural residents' electricity consumption (Song, 2025).

The coefficient of urbanization rate is significantly positive, as urbanization enhances agricultural TFP through technology diffusion and labor transfer (Bryan et al., 2014; Qiao & Lu, 2023). The coefficient of rural residents' educational level is significantly positive, as higher educational levels of farmers are more conducive to technological progress and thereby improve agricultural productivity (Wang, 2024; Asadullah & Rahman, 2009). The coefficients of disaster impact and agricultural planting

structure are not significant, as agricultural insurance offsets the impact of disasters on agricultural productivity (He, 2024). The insignificance of agricultural planting structure may be due to the fact that the selected indicators for planting structure are too simplistic and fail to consider the diversity of crops (Dong et al., 2025; Pingali, 2012).

The findings of Jin et al. (2022) show that agricultural insurance has raised the regional agricultural TFP level and significantly mediated the process of agricultural economic growth when compared to previous studies, such as the effect of agricultural insurance on the total factor productivity of agriculture. Using the Logit model, Li et al. (2022) examined how agricultural insurance affected family farms' adoption of agricultural technology. The findings indicated that agricultural insurance could have a major impact on farmers' technological advancement by altering the economic entities' income expectations. Zheng et al. (2023) found that by encouraging agricultural technology advancement, agricultural insurance might raise agricultural TFP.

For research on agricultural insurance as a threshold variable, the research results of Ma et al. (2023) indicate that agricultural insurance exhibits a threshold effect in the process of climate change affecting the credit risks of rural financial institutions. There search results of Zhou et al. (2023) show that agricultural insurance has a dual threshold effect on rural revitalization.

In conclusion, the above research is consistent with the conclusion of this study. Agricultural insurance has a threshold effect on the total factor productivity of agriculture. There is a non-linear influence relationship between agricultural insurance and the total factor productivity of agriculture. When the level of agricultural insurance reaches a certain

threshold, the promoting effect of agricultural insurance on the total factor productivity of agriculture will further strengthen.

4.8 Summary of Chapter

This chapter first measures agricultural total factor productivity using the DEA-Malmquist method, using data from 31 Chinese provinces as samples. It then examines the effect of agricultural insurance on agricultural total factor productivity. Four significant results are explained by the findings. First, the advancement of agricultural technology is the primary driver of China's increased total factor agricultural output. Second, it is demonstrated that agricultural insurance significantly promotes the growth of agricultural total factor production using the correlation test and baseline fixed effect regression analysis. Third, a regression analysis of the regulatory effect was conducted by introducing country governance and moral hazard. The results showed that while an increase in moral hazard will weaken the role of agricultural insurance on agricultural TFP, an improvement in country governance ability can strengthen the role of agricultural insurance on agricultural TFP. Fourth, the link between agricultural insurance and total factor productivity in agriculture is non-linear. Agricultural insurance will have a stronger promoting influence on agricultural total factor productivity if its level exceeds a particular threshold.

CHAPTER 5

CONCLUSION AND POLICY IMPLICATIONS

5.1 Introduction

This chapter concludes the study by summarizing the main findings, discussing their theoretical and practical implications, and providing relevant policy recommendations. Drawing on the empirical results and theoretical framework developed in the previous chapters, this section highlights how agricultural insurance affects total factor productivity across Chinese provinces and explores the broader significance of these findings in the context of agricultural modernization and risk management. The chapter also outlines limitations of the study and offers suggestions for future research.

5.2 Summary of Findings

A sample panel of 31 Chinese provinces from 2007 to 2023 was chosen as the research sample for this study. The fixed-effect model is chosen to perform empirical research on the impact of agricultural insurance on agricultural TFP and its trajectory, as well as the moderating effects of moral hazard and country governance on the influence and threshold effect of agricultural insurance on agricultural total factor productivity, based on theoretical summary and index measurement. To further examine the impact of agricultural insurance on agricultural TFP in various locations, robustness tests were conducted using four distinct methodologies, and endogeneity tests were conducted using the GMM model. The following was a summary of the key findings.

First, China's agricultural TFP from 2007 to 2023 showed a gradual growth trend on the whole, and agricultural development showed a pattern of continuous progress in technology and a slight decline in technical efficiency, that is, the growth of agricultural TFP mainly depended on the progress of agricultural technology. By studying the agricultural TFP of Chinese provinces, it is found that for provinces with high TFP, both technological change and efficiency change have high contributions to TFP, which indicates that these provinces are good in terms of technological innovation, technology adoption and resource management efficiency. For provinces with moderate and low TFP change growth, the main contribution to TFP growth is technology adoption.

Second, agricultural insurance has a significant positive impact on agricultural TFP, according to the baseline regression results using static panel data analysis. This suggests that agricultural insurance can encourage the growth of agricultural TFP and that it plays a significant role in supporting the expansion of agricultural TFP in China during the study period. The regression findings show that both agricultural technology advancement and agricultural technology efficiency are responsible for the positive effect of agricultural insurance on agricultural TFP.

Third, the moderating effects of country governance are indicated by the significantly positive interaction coefficient between agricultural insurance and country governance. This suggests that country governance has a positive regulatory effect on the relationship between agricultural insurance and agricultural TFP, and that the positive impact of agricultural insurance on agricultural TFP can be strengthened by raising the level of country governance.

Fourth, based on the results of the moderating effect model, the interaction coefficient between agricultural insurance and moral hazard is significantly negative, indicating that moral hazard has a negative moderating effect on the relationship between agricultural insurance and agricultural TFP, and the increase of moral hazard inhibits the positive impact of agricultural insurance on agricultural TFP.

Fifth, according to the findings of the threshold effect of agricultural insurance on agriculture's overall factor production. The relationship between agricultural insurance and total factor production in agriculture is nonlinear. Agricultural insurance will have a stronger promoting influence on agricultural total factor productivity if its level exceeds a particular threshold.

5.3 Policy Implications and Recommendations

Based on the empirical findings of this study, which demonstrate that agricultural insurance significantly promotes agricultural total factor productivity (TFP), that this effect is strengthened by higher levels of country governance and weakened by moral hazard behavior, policy implications should be derived in a manner that directly reflects these relationships. Accordingly, this section reorganizes the policy recommendations into three subsections corresponding to the core research findings: agricultural insurance development, country governance enhancement, and moral hazard mitigation.

5.3.1 Improving Agricultural Insurance Development to Enhance Productivity Growth

The empirical results show that agricultural insurance has a significant and positive impact on agricultural TFP, and that this effect becomes stronger once insurance

development exceeds a certain threshold level. This finding implies that agricultural insurance can effectively promote productivity growth only when it reaches sufficient scale, coverage depth, and operational maturity. Therefore, policymakers should continue to expand agricultural insurance coverage, improve premium subsidy mechanisms, and encourage broader farmer participation, particularly in regions where insurance development remains below the identified threshold.

In addition, policy design should shift from a sole focus on coverage expansion toward improving the quality and efficiency of insurance products. This includes promoting insurance schemes that are more closely linked to production risks, encouraging innovation in index-based and technology-enabled insurance products, and strengthening the role of agricultural insurance in supporting technological adoption and efficiency improvement. By doing so, agricultural insurance can better fulfill its role as a productivity-enhancing risk management instrument rather than merely an income stabilization tool.

5.3.2 Strengthening Country Governance to Amplify the Effectiveness of Agricultural Insurance

The significantly positive interaction effect between agricultural insurance and country governance indicates that institutional quality plays a crucial moderating role in shaping the productivity effects of insurance. This result suggests that improvements in governance — such as stronger regulatory frameworks, better enforcement capacity, and more transparent policy implementation — can amplify the positive impact of agricultural insurance on agricultural TFP.

Accordingly, governments should focus on enhancing the institutional environment in which agricultural insurance operates. This includes improving coordination between insurance providers, local governments, and agricultural agencies; strengthening regulatory oversight to ensure fair compensation and timely claims settlement; and reducing information asymmetry through better data sharing and digital platforms. By improving governance quality, policymakers can ensure that agricultural insurance functions more efficiently and that its productivity-enhancing effects are fully realized.

5.3.3 Mitigating Moral Hazard to Safeguard Productivity Gains from Insurance

The empirical findings further reveal that moral hazard exerts a significant negative moderating effect on the relationship between agricultural insurance and agricultural TFP. This indicates that inappropriate incentives and insufficient monitoring may weaken the productivity benefits of insurance by discouraging optimal input use or reducing farmers' incentives to improve production efficiency.

To address this issue, policymakers should strengthen mechanisms aimed at mitigating moral hazard in agricultural insurance programs. Possible measures include improving contract design by incorporating differentiated premiums and deductibles, strengthening post-disaster verification and supervision, and linking insurance participation with the adoption of good agricultural practices. In addition, enhancing farmers' awareness of risk management responsibilities and improving transparency in claims assessment can help align incentives between insurers and insured farmers, thereby preserving the productivity-enhancing role of agricultural insurance.

5.4 Contribution to the Literature

Beyond its policy implications, this study makes several important contributions to the existing literature on agricultural insurance and agricultural total factor productivity (TFP).

First, this study contributes to the literature by providing comprehensive evidence on the productivity effects of agricultural insurance from a total factor productivity perspective. While much of the existing research focuses on partial productivity measures, output growth, or farmers' income, this study systematically examines agricultural insurance through the lens of agricultural TFP, thereby capturing both technological progress and efficiency change. By decomposing TFP dynamics, the study offers a more complete understanding of how agricultural insurance influences productivity growth.

Second, this study extends existing research by explicitly incorporating moral hazard and country governance as moderating factors in the insurance–TFP relationship. Although prior studies acknowledge the existence of moral hazard and institutional constraints in agricultural insurance markets, few have empirically examined how these factors condition the productivity effects of agricultural insurance. The findings reveal that country governance strengthens, while moral hazard weakens, the positive impact of agricultural insurance on agricultural TFP, thereby uncovering important institutional channels through which insurance affects productivity.

Third, this study contributes methodologically by identifying a nonlinear, threshold-dependent relationship between agricultural insurance and agricultural TFP. Unlike earlier studies that assume a linear effect of insurance, this research demonstrates

that agricultural insurance promotes productivity more strongly once its development surpasses a critical threshold. This finding adds new evidence to the emerging literature on policy effectiveness and nonlinear productivity dynamics, suggesting that the benefits of agricultural insurance depend on its scale and maturity.

Finally, by using a long panel data set covering 31 Chinese provinces from 2007 to 2023, this study provides updated and regionally heterogeneous evidence from a major developing economy. Given China's unique institutional environment, large regional disparities, and extensive policy intervention in agricultural insurance, the findings enrich the international literature by offering insights that go beyond single-country or short-period analyses and enhance the external validity of existing theories.

Taken together, this study advances the literature by integrating productivity theory, institutional analysis, and nonlinear modeling to offer a more nuanced understanding of how agricultural insurance affects agricultural TFP.

5.5 Limitations of Study

In this study, agricultural insurance is employed as the core explanatory variable, with country governance and moral hazard introduced as moderating variables, alongside a set of control variables including rural disposable income, rural electricity consumption, urbanization rate, rural human capital, disaster intensity, and agricultural planting structure. While these variables capture key economic, institutional, and risk-related determinants of agricultural productivity, other factors that may also exert significant influences—such as agricultural fiscal expenditure, openness to international markets, and the efficiency of agricultural irrigation water use—are not explicitly incorporated due to data availability

constraints. The omission of these variables may limit the precision of the estimated effects. Future research could incorporate a broader set of policy, trade, and resource-use indicators to obtain more comprehensive and reliable estimates of the determinants of agricultural productivity.

5.6 Recommendations for Future Research

Given the variable selection constraints in this study, future research could further expand the analytical framework by incorporating additional determinants of agricultural productivity. In particular, variables such as agricultural fiscal expenditure, the degree of openness to international markets, and the efficiency of agricultural irrigation water use may play important roles in shaping agricultural total factor productivity. Including these policy-, trade-, and resource-related indicators would help capture a broader set of structural and institutional influences on agricultural productivity and improve the precision and robustness of empirical estimates. Moreover, integrating these factors may facilitate a more comprehensive understanding of the interaction between agricultural insurance and other policy instruments in promoting sustainable productivity growth.

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