Dynamic Analysis of Agricultural Mechanization and Economic Growth in Shandong Province Using a VAR Model

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Abstract: To explore the relationship between agricultural mechanization and agricultural economic growth, this paper uses time series data from Shandong Province spanning 1978 to 2022. By employing Granger causality tests and constructing a VAR model, impulse response analysis and variance decomposition are used to examine the relationship between agricultural mechanization and agricultural economic growth in Shandong Province. The results indicate a bidirectional Granger causality between agricultural mechanization and economic growth, showing that they mutually influence each other with positive effects. Additionally, there exists a long-term, reciprocal dynamic relationship between the two, with the contribution of agricultural mechanization to economic growth being significantly greater than the contribution of economic growth to agricultural mechanization.

Keywords: Agricultural Mechanization, Economic Growth, VAR Model, Shandong Province

1. Introduction

Agriculture is a fundamental pillar of China's economy, crucial for national development and the well-being of the population. The mechanization of agriculture significantly enhances productivity and efficiency^[1]. Recognizing its importance, the Chinese government has consistently prioritized agricultural development. Recent policies, such as the Ministry of Agriculture and Rural Affairs' 2020 opinion on accelerating mechanized facility planting and the 2021 "14th Five-Year" national agricultural mechanization development plan, underscore the push towards comprehensive, high-quality, and efficient mechanization. The 2024 Central Document No. 1 further emphasizes the need for enhancing agricultural machinery and improving subsidy policies. With the ongoing modernization of agriculture and the rural revitalization strategy, agricultural mechanization is increasingly gaining attention.

This study uses statistical data from Shandong Province to establish a VAR model that empirically analyzes the relationship between agricultural mechanization and economic growth. Through Granger causality tests, impulse response analysis, and variance decomposition, the research explores the dynamic interactions and influences between the two. The findings will contribute to the academic field by providing insights and policy recommendations to enhance agricultural mechanization and economic development.

Analyzing data from 1978 to 2022, this paper examines the current state and trends of agricultural mechanization and economic growth in Shandong Province. The study reveals their dynamic relationship and offers policy suggestions tailored to the region's specific context. These recommendations aim to improve production efficiency, reduce labor and material costs, and boost agricultural output and farmers' income, ultimately enhancing agricultural economic benefits. Furthermore, promoting mechanization through relevant policies will support the broader agricultural modernization process, ensuring robust implementation of national agricultural strategies.

2. Overview of Research on Mechanization and Economic Growth

2.1 Review of domestic studies

In recent years, as China's agricultural modernization has advanced and the rural revitalization strategy has been deeply implemented, the issue of agricultural mechanization and economic growth has garnered significant attention from scholars, resulting in numerous related studies. These studies can be broadly categorized into three areas: the relationship between agricultural mechanization and economic

growth, the relationship between agricultural mechanization and farmers' income, and the contribution and relationship analysis of agricultural mechanization to economic growth. For instance, Wu et al. analyzed 30 years of data from Guangxi using a VAR model and found a long-term, mutual dynamic relationship between agricultural mechanization and economic growth, with both exhibiting selfreinforcing and mutually promoting effects, and the influence of agricultural mechanization on economic growth being significantly greater than the reverse^[2]. Lin et al. conducted an empirical analysis in Heilongjiang Province, discovering that agricultural mechanization and non-agricultural income are mutually Granger causal^[3]. The development of agricultural mechanization consistently promotes nonagricultural income, while increases in non-agricultural income significantly inhibit the development of agricultural mechanization. Wang et al analyzed the contribution of agricultural mechanization to economic growth, pointing out that the application of agricultural mechanization not only effectively enhances productivity and saves labor but also promotes the scale of agricultural production, reducing resource waste^[4].

In summary, most domestic studies focus on the relationship between agricultural mechanization and farmers' income, with many qualitative analyses, factor analyses, contribution analyses, and relationship discussions. However, there are fewer studies that delve into the dynamic interaction and processes between agricultural mechanization and economic growth. Furthermore, most of these studies are conducted at the national level, with fewer at the provincial level. Therefore, this paper introduces a VAR model, utilizing Granger causality tests, impulse response analysis, and variance decomposition to deeply explore the relationship between agricultural mechanization and economic growth in Shandong Province.

2.2 Theoretical analysis

This study, based on data from Shandong Province spanning from 1978 to 2022, employs a VAR model for empirical analysis. Before conducting the empirical analysis, a theoretical examination is conducted to elucidate the relationship between agricultural mechanization and economic growth. Theoretically, the advancement of agricultural mechanization significantly promotes agricultural economic growth by increasing production efficiency, reducing production costs, and boosting agricultural output. Additionally, agricultural mechanization fosters innovation and progress in agricultural technology, providing new possibilities for agricultural production. On the other hand, economic growth in agriculture can reciprocally enhance the level of agricultural mechanization. As the agricultural economy grows, the income of both the government and farmers increases, offering more financial support for mechanization development. Furthermore, economic growth drives innovation and improvement in agricultural machinery, enhancing its performance and quality to meet production needs. Therefore, theoretically, there exists a bidirectional influence between agricultural mechanization and economic growth, with both aspects mutually reinforcing and interacting with each other.

3. Data Analysis of Agricultural Mechanization and Economic Growth

3.1 Agricultural Growth and Mechanization in Shandong

This study utilizes annual data from 1978 to 2022 on agricultural output value and the total power of agricultural machinery in Shandong Province, sourced from the official National Bureau of Statistics website. The differing units of measurement—billions of yuan for agricultural output value and billions of watts for total power of agricultural machinery—could affect the analysis. To address this, we normalize the data using mean normalization, calculated as X/Mean. For our econometric analysis, we select key indicators for agricultural mechanization and economic growth. The total power of agricultural machinery, a commonly used measure in existing literature, represents the level of mechanization (JXH). For agricultural economic growth, we use the agricultural output value (NYCZ) as the indicator. These selections are based on previous research and data availability.



Figure 1: Agricultural Output Value and Total Power of Agricultural Machinery in Shandong Province from 1978 to 2022

As shown in Figure 1, since 1978, the agricultural economy of Shandong Province has grown rapidly. Although there have been minor fluctuations in some years, the overall trend is one of rapid growth. The agricultural output value increased from 10.222 billion yuan in 1978 to 1,213.071 billion yuan in 2022, nearly a 118-fold increase, with an average annual growth rate of 11.47%. Meanwhile, the total power of agricultural machinery in Shandong Province also grew significantly, rising from 1.085 billion watts in 1978 to 11.53 billion watts in 2022, almost a tenfold increase, with an average annual growth rate of 5.52%. However, this growth rate is lower than that of the agricultural output value, and there was a sudden sharp decline in 2016, after which it began to slowly increase again until 2022. Overall, while the agricultural economy in Shandong Province has grown extremely rapidly, the level of agricultural mechanization has not kept pace with this economic growth.

3.2 Data Stationarity Test

Since the primary prerequisite for establishing a VAR model is that the selected variables must be stationary time series, it is essential first to test whether the analyzed series variables are stationary^[5]. This requires performing a unit root test to prevent the occurrence of "spurious regression" caused by non-stationary series. The commonly used DF test cannot ensure that the residuals in the equation are white noise, so Dickey and Fuller extended the DF test to form the ADF (Augmented Dickey-Fuller) test, which is now widely used for unit root testing. In this study, the ADF method is used to conduct unit root tests on the time series of agricultural output and total power of agricultural machinery in Shandong Province. If non-stationary series are detected, differencing methods will be employed to stabilize the series. The unit root test and subsequent model analysis are performed using Eviews 7 software.

Variable	ADF Test	1% Critical	5% Critical	10% Critical	P-	Test
Series	Value	Value	Value	Value	Value	Conclusion
NYCZ	-1.150455	-4.186481	-3.51809	-3.189732	0.0070	Non-
					0.9079	Stationary
ΔNYCZ	-3.718923	-4.186481	-3.51809	-3.189732	0.0316	Stationary
JXH	-1.359196	-4.180911	-3.515523	-3.188259	0.8501	Non-
					0.8391	Stationary
ΔJXH	-5.936383	-4.186481	-3.51809	-3.189732	0.0001	Stationary

Table 1: ADF test results

Based on the results shown in Table 1, the ADF test value for the original NYCZ variable series is - 1.150455, which is greater than the critical values at the 1%, 5%, and 10% significance levels. Additionally, the P-value is 0.9079, which is greater than 0.05, indicating that the NYCZ series is non-stationary. However, after taking the first difference, the ADF test value becomes -3.718923, which is less than the critical values at the 5% and 10% significance levels. The P-value is 0.0316, which is less than 0.05, indicating that the series becomes stationary after the first difference.

Similarly, for the original JXH variable series, the ADF test value is -1.359196, which is greater than the critical values at the 1%, 5%, and 10% significance levels. The P-value is 0.8591, which is greater than 0.05, indicating that the JXH series is non-stationary. After taking the first difference, the ADF test

value is -5.936383, which is less than the critical values at the 1%, 5%, and 10% significance levels. The P-value is 0.0001, which is less than 0.05, indicating that the series becomes stationary after the first difference.

3.3 Construction of the VAR Model

After testing the stationarity of the variable series, it is essential to determine the optimal lag length for the VAR model estimation to ensure the credibility of the model's results. When selecting the lag length, it is generally preferred that the lag length is sufficiently large to better capture the dynamic characteristics of the model. However, if the lag length is too large, the number of parameters to be estimated in the model increases, reducing the model's degrees of freedom.

Lag Order	LogL	LR	FPE	AIC	SC	HQ
0	-53.78094	NA	0.059895	2.860561	2.945872	2.891170
1	93.18503	271.3218	3.92e-05	-4.471027	-4.215094*	-4.379201
2	98.10083	8.571144	3.75e-05	-4.517991	-4.091437	-4.364947
3	98.65339	0.906772	4.50e-05	-4.341200	-3.744024	-4.126938
4	100.5557	2.926639	5.06e-05	-4.233626	-3.465828	-3.958147
5	105.4568	7.037485	4.90e-05	-4.279837	-3.341417	-3.943140
6	122.7435	23.04886*	2.53e-05*	-4.961203*	-3.852162	-4.563288*

Table 2: Determination of lag order for the VAR model

Note: * indicates the criterion selected

In this study, the optimal lag length for the VAR model is determined by following the principle of majority rule based on comprehensive judgments: maximizing the LR, and minimizing the FPE, AIC, SC, and HQ criteria. As can be seen from Table 2, four out of five criteria indicate that the optimal lag length is six. Therefore, the optimal lag length for the VAR model of NYCZ and JXH is determined to be six, and a VAR(6) model can be established.

4. Dynamic Analysis of Agricultural Mechanization and Economic Growth

4.1 Granger Causality Testing

After determining the optimal lag order for the VAR model, it is necessary to test the significance of the model. If the lagged values of a variable in the VAR model do not significantly affect the explained variable, the model is considered meaningless. Therefore, this study employs the Granger causality test to evaluate the VAR model established above and thus determine its validity. If the two variables are not Granger causes of each other, it indicates that the variables are exogenous, making the VAR model meaningless.

The choice of lag periods in the Granger causality test is often arbitrary, and this choice can greatly impact the test's effectiveness. However, the lag period selection in the Granger causality test based on the VAR model is determined, which effectively resolves the issue of lag period selection in the Granger causality test. Referring to the optimal lag order determined above for the VAR model, we conducted a Granger causality test on the VAR(6) model. The test results are shown in Table 3. As seen in Table 3, there is a bidirectional Granger causality between JXH and NYCZ, meaning JXH is a Granger cause of NYCZ, and NYCZ is also a Granger cause of JXH. In other words, the improvement in agricultural mechanization promotes the growth of agricultural output value, and the increase in agricultural output value also fosters the improvement in agricultural mechanization. This mutual feedback relationship aligns with the theory of agricultural economic development.

Null Hypothesis	Lag Period	Degrees of Freedom	F- Value	P- Value	Conclusion
JXH is not the Granger cause of NYCZ	6	38	2.005 36	0.102 8	Reject Null Hypothesis
NYCZ is not the Granger cause of JXH	6	38	1.768 36	0.146 7	Reject Null Hypothesis

Table 3: Granger Causality Test Results

Typically, the development of agricultural mechanization in a country or region reflects the progress of modern agriculture, which is closely related to agricultural output value. As the level of agricultural

mechanization improves, agricultural output value tends to increase. Simultaneously, the increase in agricultural output value directly raises farmers' income, thereby further promoting the development of agricultural mechanization. Based on the above tests, considering the existence of Granger causality between the variables in the VAR(6) model, the establishment of this model is deemed meaningful.

4.2 Stability Test of the Model

Inverse Roots of AR Characteristic Polynomial



Figure 2: AR Characteristic Root Test Results for the VAR(6) Model

Since subsequent impulse response and variance decomposition can only be performed if the VAR model is stable, any predictions made with an unstable model would be meaningless. Therefore, after confirming the significance of the VAR model, it is necessary to test its stability. This study uses the unit circle method to conduct the stability test on the established VAR model. The test results are shown in Figure 2, where the modulus of the inverse roots of all characteristic roots is less than 1, indicating that they are all within the unit circle. This demonstrates that the constructed VAR model has good stability and a high degree of fit. Consequently, we can proceed with impulse response analysis and variance decomposition.

4.3 Impulse Response Analysis in the VAR Model



Figure 3: (a) Response of NYCZ to Shocks from NYCZ; (b) Response of JXH to Shocks from NYCZ; (c) Response of NYCZ to Shocks from JYH; (d) Response of JXH to Shocks from JXH.

In a VAR model, impulse response analysis is used to evaluate the time and magnitude of one variable's impact on another. Conducting impulse response function analysis can further determine the authenticity of the causal relationship between variables. Below, we analyze the impulse responses between the two variables involved in the established VAR model. The analysis results are shown in Figures 3, where the horizontal axis represents the number of lags, set to 10 periods here, and the vertical axis represents the impulse response. The solid line represents the impulse response function, while the dashed lines represent the bands of plus and minus two standard deviations.

Figure 3(a) shows the response of NYCZ to its own shocks. The figure indicates that NYCZ's response to its own shocks has a significant positive effect. The response of NYCZ to its own shocks starts at 0.046 in the first period and then gradually increases, reaching a maximum value of 0.076 in the third and fourth periods. Afterward, it begins to decline gradually, reaching a minimum value of 0.002 in the eighth period, before starting to rise again. Overall, NYCZ's response to its own shocks has a long-term, significant positive effect.

Figure 3(b) shows the response of NYCZ to shocks from JXH. The figure indicates that NYCZ's response to shocks from JXH has a significant positive effect. The response of NYCZ to JXH shocks starts at 0.057 in the first period and then gradually increases, reaching a maximum value of 0.078 in the third period. From the third to the eighth period, it fluctuates downward, reaching a low point of 0.011 in the eighth period, still above zero, before starting to rise again. Overall, NYCZ's response to JXH shocks has a long-term positive effect, indicating that continuous growth in the agricultural economy can promote a sustained increase in the level of agricultural mechanization.

Figure 3(c) shows the response of JXH to shocks from NYCZ. The figure indicates that JXH's response to shocks from NYCZ has a significant positive effect. The response of JXH to NYCZ shocks starts from zero in the first period and then rises slowly, reaching a peak of 0.023 in the fifth period. Between the fifth and seventh periods, there is a trough, with the sixth period being the lowest at 0.003. Afterward, it rises quickly from the seventh period, reaching 0.088 in the tenth period. Overall, JXH's response to NYCZ shocks has a long-term positive effect, although this positive effect is lower in the early periods. This indicates that the promotion effect of agricultural mechanization on agriculture is not fully realized initially, but it becomes more evident after some time.

Figure 3(d) shows the response of JXH to its own shocks. The figure indicates that JXH's response to its own shocks has a significant positive effect. The response starts at 0.082 in the first period, and the impulse function generally fluctuates around the level of 0.09, reaching a maximum of 0.112 in the ninth period, which is not significantly different from 0.09. Overall, JXH's response to its own shocks has a positive effect that remains stable over the long term, indicating that agricultural mechanization has a relatively stable self-reinforcing effect.

4.4 Variance Decomposition Analysis in the VAR Model

Variance decomposition analyzes the contribution of each structural shock to changes in endogenous variables, thereby evaluating the importance of different structural shocks^[6]. Here, Eviews 7 software is used to perform variance decomposition calculations, and the results for the VAR model of agricultural mechanization and economic growth in Shandong Province are shown in Table 4.

Period	Variance Decomposition of NYCZ			Variance Decomposition of JXH			
	S.E.	NYCZ	JXH	S.E.	NYCZ	JXH	
1	0.045776	100.000000	0.000000	0.045776	32.125790	67.874210	
2	0.084794	99.930700	0.069300	0.084794	30.328920	69.671080	
3	0.114180	99.672570	0.327430	0.114180	36.424680	63.575320	
4	0.137953	98.489400	1.510596	0.137953	32.879570	67.120430	
5	0.155644	96.693360	3.306638	0.155644	31.641180	68.358820	
6	0.158827	96.779190	3.220813	0.158827	30.479610	69.520390	
7	0.159089	96.669020	3.330981	0.159089	27.534520	72.465480	
8	0.162463	92.717560	7.282438	0.162463	25.244070	74.755930	
9	0.174467	82.233870	17.766130	0.174467	23.039890	76.960110	
10	0.200076	67.321210	32.678790	0.200076	21.154740	78.845260	

Table 4: Variance Decomposition Results of NYCZ and JXH

From the variance decomposition results of NYCZ and Figure 4 it can be seen that the contribution of NYCZ to itself gradually decreases over time. From the first period to the eighth period, the decline is

slow, with NYCZ's contribution to itself being 100% in the first period and decreasing to 92.717560% by the eighth period, still remaining above 90%. However, from the eighth period onwards, the rate of decline accelerates, and by the tenth period, the contribution has decreased to 67.321210%. Conversely, the contribution of JXH to NYCZ shows a gradual increase over time, which is the opposite trend of NYCZ's contribution to itself. The contribution of JXH to NYCZ starts at 0% in the first period and increases slowly over the first eight periods, reaching 7.282438% in the eighth period. From the eighth period onwards, the rate of increase accelerates, and by the tenth period, the contribution reaches 32.678790%. This indicates that JXH has a significant and positive impact on NYCZ, but the initial impact is low, and this positive effect becomes more pronounced over time.



Figure 4: (a) Variance Decomposition Results of NYCZ; (b) Variance Decomposition Results of JXH.

From the variance decomposition results of JXH and Figure 4, it can be seen that the contribution of JXH to itself generally shows an upward trend. There is a fluctuating decline from the first period to the third period, starting at 67.874210% in the first period, rising slightly in the second period, and then decreasing to 63.575320% in the third period. From the third period onwards, the contribution begins to increase slowly, and by the tenth period, it reaches 78.845260%. This indicates that JXH has a strong self-reinforcing function, and this function strengthens over time. In contrast, the contribution of NYCZ to JXH shows a slow downward trend. From the first period to the third period, there is a fluctuating rise, starting at 32.125790% in the first period, decreasing slightly in the second period, and then increasing to 36.424680% in the third period. From the third period onwards, the contribution decreases slowly, and by the tenth period, still accounting for about one-fifth. This indicates that NYCZ has a long-term positive effect on JXH, but this effect gradually decreases over time and stabilizes at a certain level.

5. Conclusions

Based on the time series data of agricultural mechanization and economic growth in Shandong Province from 1978 to 2022, this study establishes a VAR model between the total power of agricultural machinery and agricultural output value. The Granger causality test reveals a bidirectional relationship, where agricultural mechanization and economic growth mutually promote each other. Impulse response analysis indicates that both have long-term positive effects on each other, with impacts growing stronger over time. Variance decomposition shows that agricultural mechanization contributes more significantly to economic growth than vice versa. The contribution of agricultural mechanization to economic growth increases from 0% in the first period to 32.68% in the tenth period, while the contribution of economic growth to agricultural mechanization stabilizes around 21.15%.

Agricultural mechanization is key to modern agriculture and economic development in China. To enhance its role in Shandong Province, this paper recommends aligning machinery subsidy policies with the "14th Five-Year Plan." Addressing issues such as an excess of low-end machinery and insufficient supporting equipment requires differentiated subsidies that favor high-end modern machinery. Encouraging the production of advanced, energy-efficient machinery while phasing out inefficient equipment is essential. Additionally, improving agricultural infrastructure and land management through policy guidance and investment will support mechanization. Promoting sustainable agricultural economic development through financial support, adjusting economic structures, and encouraging large-scale, mechanized farming will further enhance mechanization efforts.

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