SVAR Metrics Analysis for the Impact of Fintech on Rural Economy Growth

Yu Duan[a], Yuxin Liu[b] and Jinchuan Ke[c]
School of Economics & Management, Beijing Jiaotong University, 100044, Beijing, China

Keywords: Fintech, SVAR, Impulse Function.

Abstract: The Fintech (financial technology) has the characteristics of low transaction costs, high transaction efficiency and strong assistance. In the past decade, it has gradually become one of the main forms of Fintech. Based on the background of the rapid development of Fintech, this article discusses the impact mechanism of Fintech on rural economic development from the perspective of the development scale of internet third-party payment and P2P network loans. The results of the research show that the impact of Fin-tech on the development of the rural economy is weak in the short-term and strengthened in the long-term. The results of the impulse response show that the positive changes in rural economic growth itself, third-party payments and P2P network loans can significantly promote local economic development.

1 INTRODUCTION

Fintechs such as P2P and crowd funding platform have injected new vitality into finance and related industries from all aspects. It is not difficult to find that the sudden emergence of Fintech (financial technology) is significantly impacting the existing profit model of traditional financial institutions. The rural market is an indispensable part of the internet economic system, and the development of Fintech can greatly meet the innovation needs of its financial service system. In addition, the innovative characteristics of Fintech itself are compatible with the ideas for the transformation and upgrading of my country's rural economy, and can help the rural economy move towards high efficiency and high quality. Driven by innovation, the development mode of "Internet + modern countryside" has become commonplace. Financial institutions are actively deploying rural areas. From the perspective of econometrics, this article takes the entire rural economic development as an explanatory variable, and uses the SVAR model to empirically analyze the relationship between Fintech and the rural economy.

2 LITERATURE REVIEW

In the context of global economic integration, the economic ties between different regions and industries are closer, and financial technology and its service products are continuously integrated with the real economy (Li 2015). Industry 4.0 is the fourth industrial revolution, which is closely related to the Internet of things (IOT), communication technology (ICT) and enterprise architecture (EA). Therefore, fintech has also developed rapidly with industry 4.0 (Lu 2017). In the era of industry 4.0, through fintech, all forms of financial transactions not only make faster, easier and more efficient, but also make a positive contribution to improving public financial services and help promote the economy in the digital age (Mardiana 2020).

Many scholars have carried out detailed interpretation and analysis of Fintech risk, and successfully applied it to real economic development research. For example, Ying (2016), Kai (2016) and Xianyu (2018) believes that Fintech has developed rapidly in recent years, but it needs to be strictly regulated by the government. Ting (2017) believes that the theory of rural finance still needs to be

[a] https://orcid.org/0000-0001-7465-5323
[b] https://orcid.org/0000-0003-0809-9685
[c] https://orcid.org/0000-0001-6747-6968

Duan, Y., Liu, Y. and Ke, J.
SVAR Metrics Analysis for the Impact of Fintech on Rural Economy Growth.
DOI: 10.5220/0011188300003440
In *Proceedings of the International Conference on Big Data Economy and Digital Management (BDEDM 2022)*, pages 497-502
ISBN: 978-989-758-593-7

developed in depth, and that the government's timely and appropriate intervention is particularly needed to help traditional and new rural financial institutions embark on the development path of inclusive finance. The view point of Jianbing (2018) is that Fintech has become a new vitality in rural economic development from budding to vigorous development in just a few years. Wenqi (2018) combed and summarized the theory of rural finance, summarized and analyzed the development process and current situation of rural finance, constructed a panel model to study the mechanism of rural financial development and farmers' income growth. Yongcang (2021) deeply analyzed the evolution process and structural changes of rural household income growth, the characteristic facts and evolution trends of digital finance, and constructed a theoretical framework for the influence of digital finance on household income growth.

3 SVAR MODEL

The Vector Auto Regressive Model to study the interaction between two or more variables is referred to as VAR model. The VAR model is essentially a multivariate data analysis method, which takes each endogenous variable in the system as a function of the lag value of all endogenous variables in the system. Therefore, this model successfully extended the univariate autoregressive model to the vector autoregressive model composed of multiple time series variables. If the VAR model is not based on strict economic theory, the explanatory variables are all lagged terms, and no parameter constraints are imposed, then it can avoid identification problems and endogenous explanatory variable problems, so it is structural and non-restrictive, and is recorded as SVAR. The important premise of the realization of the VAR model is that the time series corresponding to all variables are stable. Therefore, this paper uses the ADF unit root test method to test the stationarity of the selected time series and their difference terms. Its basic form is as follows:

$$\Delta Y_t = \beta_0 + \gamma t + \emptyset Y_{t-1} + \sum_{i=1}^{m} \beta_i \Delta Y_{t-i} + \delta_t \quad (1)$$

Where, $\emptyset = 0$, the original series is a non-stationary series, and $\emptyset < 0$, the original series is a stationary series. The general mathematical formula of the SVAR model is shown as follows, setting the number of variables as N and the lag order as p, where c is the n-dimensional constant column term, ε_t is the n-dimensional error column vector, the coefficient α is a matrix of $N \times N$:

$$Y_t = c + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \alpha_3 Y_{t-3} + \cdots + \alpha_p Y_{t-p} + \varepsilon_t \quad (2)$$

Where, $Y_t = (y_{1,t}, y_{2,t}, y_{3,t}, \cdots, y_{n,t})$, $c = (c_1, c_2, c_3, \cdots, c_n)$,

$\varepsilon_t \sim \Pi N(0, \Omega)$, $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t}, \cdots, \varepsilon_{n,t})$.

$$\Pi_j = \begin{bmatrix} \pi_{11,j} & \cdots & \pi_{1N,j} \\ \vdots & \ddots & \vdots \\ \pi_{N1,j} & \cdots & \pi_{NN,j} \end{bmatrix}, j = 1,2,3, \cdots, p \quad (3)$$

If the model meets the conditions: (1) The n*n-dimensional matrix formed by the coefficient is not 0 and $p > 0$; (2) The roots of the characteristic equation fall outside the unit circle; (3) ε_t are independent of each other. At this time, ε_t is an n-dimensional white noise vector sequence, also called an impact vector. $Cov(\varepsilon_t x'_{t-j}) = E(\varepsilon_t x'_{t-j}) = 0$, (j=1,2,3,⋯) , that is, the lag period of x_t, x_t and ε_t is not correlated.

In order to solve the problem of correlation between the random error terms corresponding to different equations, we usually use Cholesky decomposition to attribute the relevant part to the random disturbance term of the first variable in the SVAR system. Processing in this way can make the random error terms corresponding to different equations irrelevant.

The SVAR model estimation method used in this paper is OLS estimation, and the model parameter matrix is:

$$A_i = \begin{bmatrix} a_{11,i} & \cdots & a_{1N,i} \\ \vdots & \ddots & \vdots \\ a_{N1,i} & \cdots & a_{NN,i} \end{bmatrix}, i = 1,2,3, \cdots, p \quad (4)$$

Then find the OLS estimate of the model parameter matrix $A_1, A_2, \cdots, A_p$, that is, find the $(\widehat{A_1}, \widehat{A_2}, \cdots, \widehat{A_P})$ that makes the following formula obtain the minimum value:

$$Q = \frac{1}{T} \sum_{j=p+1}^{T} \left(y_t - \sum_{j=1}^{p} \hat{A}_j y_{t-1}\right) \left(y_t - \sum_{j=1}^{p} \hat{A}_j y_{t-1}\right)' \quad (5)$$

For the order determination, this article uses the AIC and SC information criteria, also called the minimum information criterion, to determine the lag order of the SVAR model:

$$AIC = -2l/T + 2n/T, SC = -2l/T + n\ln T/T \quad (6)$$

Where, $l = -\frac{Tk}{2}(1 + \ln 2\pi) - \frac{T}{2}\ln\left|\hat{\Sigma}\right|$, n is the number of parameters that the model needs to estimate, $n = pN^2$. The minimum information criterion is to take p=1,2,3... for AIC or SC respectively. When AIC or SC=min, the corresponding p is the appropriate order of the model, and the corresponding $\widehat{A_1}, \widehat{A_2}, \cdots, \widehat{A_P}$ is the best model parameter estimation.

After establishing the SVAR model, we need to make a judgment on the stability of the SVAR model, based on the value of the characteristic root. Calculate the value of the characteristic root and compare the absolute value of its reciprocal with 1. If the absolute value of all the reciprocal of the characteristic root is less than 1, it means that the SVAR model is stable. If the absolute value of the reciprocal of the characteristic root is greater than 1, it means that the SVAR model is unstable. The stationary SVAR model can be written as a vector moving average model, denoted as VMA:

$$y_t = \mu + \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \quad (7)$$

Where, μ is the p×1 dimensional vector of the mean value of y_t, and A_i represents the impulse response matrix, which shows the response of the variable to short-term impacts of other variables, and can reflect the dynamic interaction characteristics between the variables. For the impulse response, the cumulative response function caused by the pulse of y_j is $\sum_{q=0}^{\infty} d_{ij}^{(q)}$, among them, $d_{ij}^{(q)}$ is the element in the i-th and j-th columns of $A_q(q = 0,1,2,3,\cdots)$.

The matrix can be expressed as: $A_q = \partial y_{t+q}/\partial v_t'$, that is, the element in the i-th row and j-th column of A_q is equal to the j-th variable perturbation term in the period t plus one unit. When the disturbance term in other periods is constant, the influence on the value of the i-th variable in the period t+q.

In addition, based on the estimation of the SVAR model, this paper further introduces Granger causality test to clarify whether the correlation between the variables we obtained is meaningful. The Granger causality test is aimed at estimating the following regressions in the time series:

$$y_t = \sum_{i=1}^{q} a_i x_{t-i} + \sum_{j=1}^{q} b_j y_{t-j} + u_{1t} \quad (8)$$

$$x_t = \sum_{i=1}^{s} \varphi_i x_{t-i} + \sum_{j=1}^{s} \omega_j y_{t-j} + u_{2t} \quad (9)$$

Among them, u_{1t} and u_{2t} are white noise. It is assumed that y is related to itself and the past value of x, and x is related to itself and the past value of y.

4 EMPERICAL ANALYSIS

4.1 Data Processing

This paper selects rural GDP as an indicator to measure rural economic development and analyzes it as an explanatory variable. In terms of Fintech, this paper selects representative third-party payment scale and P2P network loan transaction volume as independent variables. This article selects the 2012-2020 quarterly data for analysis. Due to the exponential trend and heteroscedasticity that may exist in the data, logarithmic processing is adopted for the transformed data. After processing, the corresponding symbols of the variables are: LNGDP (Rural economic growth), LNPAY (Third-party payment LNPAY), LNP2P (P2P network loan LNP2P).

4.2 Staionarity Test of Variables

The stationarity of the time series can effectively prevent the emergence of pseudo-regression models. In this paper, the ADF unit root test method is used to test the stationarity of the selected variables after logarithmization of the time series data. The results show that LNGDP, LNPAY, and LNP2P are all first-order single integers at the 5% confidence level, which meets the conditions for establishing the VAR model. The stationarity test results are shown in Table 1.

Table 1: Unit root test results.

Variable	t-Statistic	Prob
LNGDP	-26.5	0.0001
LNPAY	-4.47	0.0004
LNP2P	-3.37	0.0346

4.3 Lag Order Selection

The degree of freedom of the variables in the SVAR model depends on the choice of the variable lag order. The larger the lag order, the more complete the dynamic relationship between the variables shown by the model, but the increase in the variable lag order will also cause the overall degree of freedom of the model to decrease. Next, this article selects a more appropriate lag order based on the model design and selection of AIC and SC information criteria.

Through software analysis, it is found in Table 2 that the AIC value and SC value are the smallest when the lag order is 5, so the optimal lag order is 5.

Table 2: Lag order performance.

Lag order	AIC value	SC value
Level 2	-2.94	-2.66
Level 3	-2.62	-2.37
Level 4	-3.67	-3.46
Level 5	-6.03	-5.88

However, when the lag order is 4 or 5 in the characteristic root test result, there are points outside the unit circle, and when the lag order is 3, as shown in Figure 1, all points fall within the unit circle.

Therefore, the final reasonable lag order selected is 3, and the VAR model we build is stable at this time.

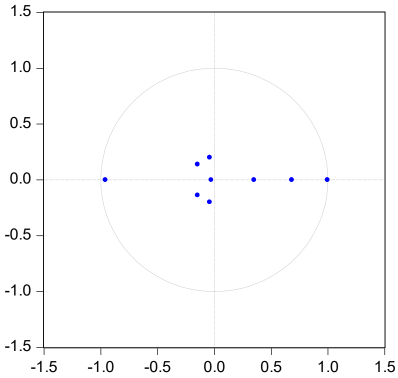

Figure 1: Roots of AR characteristic polynomials.

4.4 Granger Causality Test

After determining the lag order, the SVAR (3) model parameter estimation results are as follows.

$$\begin{aligned} LNGDP &= 0.9168 * LNGDP(-1) + 0.936 * LNGDP(-2) \\ &+ 0.6046 * LNGDP(-3) + 0.0204 * LNP2P(-1) \\ &+ 0.006 * LNP2P(-2) + 0.0638 * LNP2P(-3) \\ &+ 0.01259 * LNPAY(-1) + 0.0018 * LNPAY(-2) \\ &+ 0.0291 * LNPAY(-3) + 8.579 \end{aligned}$$

From the estimation results, rural economic growth is greatly affected by its own lagging items, but the lagging coefficients of third-party payment and P2P network loans are still positive. Therefore, the lagging items of third-party payment and P2P network loans are still affected by the level of economic growth has a positive impact. The development of Fintech has a positive impact on rural economic growth. In addition, from the perspective of the change trend of the coefficient of the lagging term, the coefficients of third-party payment and P2P network loans in the lagging three phases are slightly higher than those of the lagging phases one and two. The impact of growth has a time lag, and its positive effects will gradually appear and increase over time. Aiming at the established SVAR model, this paper uses Granger Causality/Block Exogeneity Wald Tests to test the causality between variables to clarify whether the correlation between variables is meaningful, and analyze third-party payment, P2P network loans and rural economy.

Table 3 shows the results of the Granger causality test, at a significance level of 10%, "third-party payment is not the Granger reason for rural economic development" and "P2P network loans are not the Granger reason for rural economic development" hypothesis rejected, that is to say, the development of Fintech has a significant role in promoting the transformation and upgrading of the rural economy, while the back-feeding effect of rural economic development on Fintech is not significant.

Table 3: Granger causality test results

Null Hypothesis	F-Statist.	Prob
LNPAY does not Granger cause LNGDP	23.894	0.0007
LNGDP does not Granger cause LNPAY	0.6944	0.5308
LNP2P does not Granger cause LNGDP	3.8763	0.0736
LNGDP does not Granger cause LNP2P	0.3628	0.7081
LNP2P does not Granger cause LNPAY	0.8465	0.4686
LNPAY does not Granger cause LNP2P	1.8084	0.2327

4.5 Impulse Response Analysis

Through the impulse response function of the SVAR model, the time path of the response function of each variable in the model can be analyzed. Figure 2 shows the economic growth impulse response function. Figure 3 shows the impact of P2P network loans on rural economic growth.

From the impulse response results in Figure 2, Figure 3, and Figure 4, it can be seen that rural economic growth responds to its own disturbances or shocks to a greater extent, while third-party payment and P2P network loans have less impact on the changes in rural economic growth. But from the result point of view, the solid line is above the axis, so the effects of the variables are in the same direction.

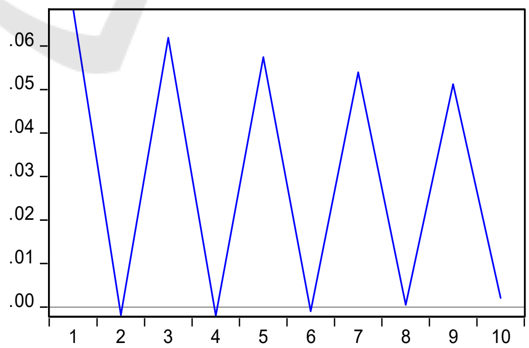

Figure 2: Economic growth impulse response function.

(LNGDP to LNGDP)

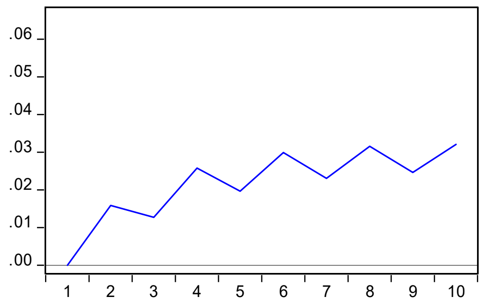

Figure 3: Economic growth impulse response function.

(LNGDP to LNP2P)

The impact of third-party payment on the growth rate of the rural economy is shown in Figure 4.

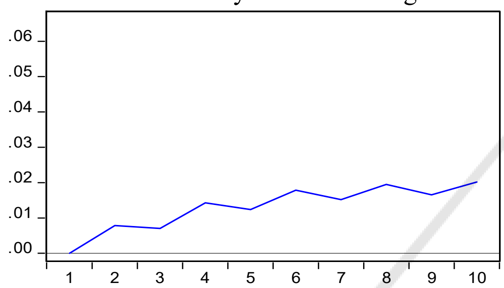

Figure 4: Economic growth impulse response function.

(LNGDP to LNPAY)

Third-party payment and P2P network loans can promote rural economic development. In addition, the first-phase response value of the impulse response results of third-party payment, P2P network loans and rural economic growth is 0, which shows that the impact of third-party payment and P2P network loans on rural economic development is lagging. This is because Fintech to inject capital or provide financial services for the development of rural related industries does not have immediate effect. It needs to go through production, market and other links to gradually emerge. As time goes by, the response value shows a gradual upward trend, which shows that from a long-term perspective, The development of rural Fintech has a significant positive effect. The variance analysis can be seen in Table 4.

Table 4: Variance analysis results.

Period	S.E.	LNGDP	LNP2P	LNPAY
1	0.04799	100.0000	0.00000	0.00000
2	0.06098	74.0808	3.31968	22.5994
3	0.06558	71.2910	8.54267	20.1662
4	0.08073	51.2922	8.04840	40.6593
5	0.08526	55.2787	8.25947	36.4617
6	0.09907	41.3591	9.94682	48.6940
7	0.10433	47.0140	8.99896	43.9870
8	0.11634	37.8143	11.6640	50.5216
9	0.12204	43.3885	10.6797	45.9317
10	0.13145	37.5307	13.6003	48.8689

The results show that the third-party Internet payment has the highest contribution rate to the rural economic development. In the long-term development process, the contribution to the rural economy reaches 48.87%. Followed by P2P network loans, in the long-term development process, the contribution to rural economic development reached 13.6%. The influence of rural economic development on itself has gradually weakened over time, while the influence of third-party Internet payment and P2P network loans on rural economic development has gradually increased, which further proves that the impact of Fintech on rural economic growth has a time-lag conclusion.

5 CONCLUSIONS

In this study, the results that the scale of third-party payment and whether P2P network loans have played a positive role in rural economic development, and the degree of this influence changes in a dynamic environment. The results of Granger causality test show that third-party payment and P2P network loans have a significant role in promoting rural economic development, while the back-feeding effect of rural economic development on financial innovation is not significant.

According to the results of impulse response, the positive changes of rural economic growth itself, third-party payment and P2P network loans can obviously promote rural economic development, but the promotion of rural economic growth by third-party payment and P2P network loans has a time lag. The results of variance decomposition also show that third-party Internet payment has the highest contribution rate to rural economic development.

We also find that financial innovation cannot play a significant role in promoting in the short term, so it is imperative to improve the construction of information network in rural areas and service quality of science such as e-commerce in the long term.

REFERENCES

Jianbing, L. (2018). Research on rural economic development under the background of financial innovation. Natl Circu. Econ. 31, 84-86.

Kai, W. (2016). Research on the status quo, problems and countermeasures of financial innovation in promoting rural development in taizhou city. Times Financ. 30, 58-60.

Li, J. (2015). Thoughts on Internet Finance. *Manag. World*. 07, 1-7.

Lu, Y. (2017). Industry 4.0: A Survey on Technologies, Applications and Open Research Issues. *J. Ind. Inf. Integrat.* 6, 1-10.

Mardiana, S.L., 2020. Faridatul, T., Mardiyana, L.O. The contribution of Financial Technology in Increasing Society's Financial Inclusions in the Industrial Era 4.0. *Proc. 2nd Intl. Conf. Env. Geo. Edu. (ICEGE)*. IPO Publishing Ltd.

Ting T., 2017. Research on the operation mechanism of rural inclusive finance. *Dissertation,* nanjing forest. univ.

Wenqi X., 2018. Development of rural finance in China. *Dissertation,* Tianjin Univ. Financ. & Econ.

Xianyu X. (2018). Analysis of the impact of financial innovation on economic development. Chin. Bus. Forum. 28, 42-44.

Ying Z. (2016). The impact of the new round of financial innovation reform on the rural economy. Econ. Res. Ref. 64, 73-76.

Yongcang, W., 2021. Digital finance and farmers' income growth. *Dissertation,* S. Univ.