Original Paper

A Study on the Dynamic Relationship between Digital Financial Development, Social Consumption and Economic Growth

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Abstract

With the development of the Internet, digital finance provides "efficient, responsible and commercially sustainable" financial services to more economic agents at a lower cost of capital and in a more convenient way, thus achieving the long-term goal of financial services that are both inclusive and precise in the real economy. Social consumption and economic growth are closely related, as the economy increases, so does consumption, and consumption also drives economic growth. By building a VAR model and using econometric methods, this paper empirically analyses that the three factors, namely digital economy development, social consumption and economic growth, have obvious roles and long-term dynamic relationships, but there is no good dynamic cycle between the three factors, and gives corresponding policy recommendations.

Keywords

Digital financial development, Social consumption, Economic growth, VAR model

1. Introduction

The retail trade of consumer goods is the link between producers and consumers, and it is more sensitive than other sectors to economic activities and is a barometer of national economic growth (Li, 2005). The total retail sales of consumer goods is a concrete reflection of social consumption demand, and social consumption is a major factor driving local economic development, so it is important to study the relationship between total retail sales of consumer goods and economic growth. Over the past 5-10 years, China's digital economy (especially digital finance) has undergone rapid development based on innovative technologies such as information, big data and cloud computing, such as Alipay and WeChat Pay. The creation and sharing of information or data brought about by the Internet revolution in China has helped to drive the emergence of a digital financial industry, improving the availability and accessibility of finance and thereby contributing to economic growth. This has

significantly improved the availability and accessibility of financial services, especially for those who previously did not have access to the financial markets, thus contributing to the development of financial inclusion in China. The international community has recognised the role of inclusive services provided by digital finance in promoting healthy economic development, and in 2016 the G20 Summit proposed the G20 High Level Principles for Digital Inclusive Finance, which became the first international common platform for promoting digital inclusive finance (Hu & Cheng, 2020).

2. Literature Review and Commentary

Most domestic studies on total retail sales of consumer goods have fitted statistical models for forecasting purposes, e.g., Wang et al. used the ARI-MA model to forecast total retail sales of consumer goods in China (Wang, Z. J. & Wang, B, H., 2014); given the influence of random disturbances in economic data, Pan and Shi (2015) used the grey forecasting method to forecast total retail sales of consumer goods in the future; Luo (2013) used exponential smoothing to forecast total retail sales of consumer goods from 2011 to 2013; Gui (2015) introduced a Bayesian seasonal adjustment model, and the results indicated that China's total retail sales of consumer goods had an exponential growth trend. There are also analyses on the relationship between total retail sales of consumer goods and economic variables, for example, Yang (2013) used data mining analysis to find a strong correlation between total retail sales of consumer goods and sales of goods; Zheng (2012) analysed the influence of population on total retail sales of consumer goods from the perspective of demographic factors.

The most central function of finance is to achieve optimal allocation of resources while minimising risk. Empirical findings show that financial development helps to smooth consumption, manage risk, reduce residential constraints and facilitate transactions (Levine, 2005). The digital economy, and digital finance in particular, naturally has financial characteristics as well. With the rapid development of digital finance in China, the internet-enabled financial system has significantly reduced financial transaction costs, improved the efficiency of financial resource allocation and reduced information asymmetry in the market (Shen & Huang, 2016). In addition, previous studies have shown that the digital economy contributes to financial inclusion and thus economic growth. The development of digital finance has helped improve the entrepreneurial behaviour of rural residents and brought about equalisation of entrepreneurial opportunities, and helped promote entrepreneurial behaviour among households with low physical or social capital, thus contributing to inclusive growth in China (Zhang, 2019). Using the China Digital Inclusive Finance Index, Song (2017) found that the development of digital finance helped to narrow the urban-rural income gap. Using the index, Xie et al. (2018) similarly combined with regional-level data on enterprise innovation to confirm that the development of digital finance promoted enterprise innovation. War (2020) and others also study that digital financial development improves the effectiveness of monetary policy, mainly by amplifying the magnitude of the impulse response of output to policy shocks, reducing the lag time and weakening the "price puzzle".

In summary, most studies on the digital economy use macro data to discuss the relationship between the digital economy and economic development, regional inequality and business innovation at the macro level, making it difficult to identify the micro mechanisms of the economic effects of digital finance. Apart from Yi and Zhou (2018), who found that the development of digital finance promoted residential consumption through two aspects, such as enhancing payment convenience and alleviating liquidity constraints, there is no literature examining the impact of digital finance development on social consumption for social consumption. Scholars have mainly studied the trend changes in total retail sales of social consumption, or considered only one factor in relation to total retail sales of social consumption. In view of the urgent need to restructure China's economy and the leading role of consumption in economic growth, this paper examines the relationship between digital finance, social consumption and economic growth using a VAR model. In previous studies, Zhang (2019) investigates the influence mechanism between the digital economy, inclusive finance and inclusive growth, but no scholars have linked digital economic development, social consumption and economic growth to study the relationship between the three.

3. Model Theory Analysis

3.1 Model Selection

Classical econometric models are based on some economic theory or understanding of economic behaviour to determine the theoretical relationships of the model. However, traditional regression analysis requires that the time series used must be stationary, otherwise a 'pseudo-regression' problem will arise. VAR models are constructed by treating each endogenous variable in the system as the lagged value of all endogenous variables in the system. It can be used to predict interconnected time series systems and to analyse the dynamic impact of random disturbances on the system of variables, thus explaining the impact of various economic shocks on the formation of economic variables.

3.1.1 VAR Model

General representation of the VAR model.

The expression for a VAR model containing k time series with a lag order of p is

$$Y_t = \mu + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \varepsilon_t \quad t = 1, \ldots\ldots, T$$

where $E(\varepsilon_t) = 0$, $E(\varepsilon_t, Y_{t-1}) = 0$; Y_t is a linear stochastic process with homoskedasticity consisting of (n × 1) vectors, βi is the coefficient matrix of (n × n), Y_{t-1} is Y_t a lagged variable of order i of the vectors, and ε_t is a random perturbation term.

Therefore, in building the VAR model, steps such as smoothness test, optimal lag judgment, co-integration test and Granger causality test are performed.

3.1.2 Stability Check

For a time series to build a VAR model, it must be a smooth time series before proceeding to the next step. So first test its smoothness, which has three general forms, divided into.

Model 1. $\Delta X_t = \delta X_{t-1} + \sum_{i=1}^{m} \beta_i \Delta X_{t-i} + \varepsilon_t$

Model 2. $\Delta X_t = \alpha + \delta X_{t-1} + \sum_{i=1}^{m} \beta_i \Delta X_{t-i} + \varepsilon_t$

Model 3. $\Delta X_t = \alpha + \beta T + \delta X_{t-1} + \sum_{i=1}^{m} \beta_i \Delta X_{t-i} + \varepsilon_t$

where T is a time variable that represents some trend in the time series over time. The null hypotheses are all $H_0: \delta = 0$, i.e. there is a unit root. The actual tests are performed in the order of model 3, model 2 and model 1. When the test rejects the null hypothesis that there is no unit root in the original series and that it is a smooth series, and when to stop the test.

3.1.3 Co-integration Test

In order to test whether the two variables yt, xt are cointegrating series, Engle and Granger proposed the E-G two-step test in 1987.

In the first step, the sequences yt and xt are both single integers of order 1, and the following equation is estimated using OLS methods:

$yt = \widehat{\alpha} + \hat{\beta} \, xt + \varepsilon_t$

Using $\widehat{\alpha}$ and $\hat{\beta}$ to denote the estimated values of the regression coefficients, the model residuals are:

$\varepsilon_t = y_t - \widehat{\alpha} + \hat{\beta} x_t$

The second step is to test for cointegration. If ε_t it is a smooth series, then the two variables yt, xt are considered to be cointegrated of order (1, 1); the regression equation obtained in the first step above is called the cointegration equation.

3.1.4 Granger's Causality Test

For the relationship between the three variables studied in this paper (LNGDP, LNTSC, LNIF), the estimated models for the Granger causality test are

$$LNGDP_t = \beta_0 + \sum_{i=1}^{m} \beta_i \, LNTSC_{t-i} + \sum_{i=1}^{m} \alpha_i \, LNTSC_{t-i} + \mu_t$$

$$LNGDP_t = \gamma_0 + \sum_{i=1}^{m} \gamma_i \, LNIF_{t-i} + \sum_{i=1}^{m} \lambda_i \, LNIF_{t-i} + \epsilon_t$$

$$LNIF_t = \delta_0 + \sum_{i=1}^{m} \delta_i \, LNTSC_{t-i} + \sum_{i=1}^{m} \kappa_i \, LNTSC_{t-i} + \nu_t$$

$$LNTSC_t = \rho_0 + \sum_{i=1}^{m} \rho_i \, LNIF_{t-i} + \sum_{i=1}^{m} \sigma_i \, LNIF_{t-i} + \pi_t$$

$$LNIF_t = A_0 + \sum_{i=1}^{m} A_i \, LNGDP_{t-i} + \sum_{i=1}^{m} B_i \, LNGDP_{t-i} + \theta_t$$

$$LNTSC_t = \varphi_0 + \sum_{i=1}^{m} \varphi_i\, LNGDP_{t-i} + \sum_{i=1}^{m} \phi_i\, LNGDP_{t-i} + \omega_t$$

The Granger causality test between two variables (X, Y) in the time series case, if the past information of variables X and Y is included, the prediction of variable Y is better than the prediction of Y by past information of Y alone, i.e. variable X helps to explain the future change of variable Y and X is considered to be the Granger cause of Y.

4. Research Methodology and Data Sources

4.1 Research Methodology

Since traditional regression methods, cannot accurately explain the dynamic relationships between multiple variables, this study chose vector autoregressive (VAR) models and other econometric methods to conduct the analysis.

4.2 Data Sources and Selection of Variables

4.2.1 Digital Economy Development (IF/Trillion RMB)

Some scholars in China have chosen to use the "China Digital Financial Inclusion Development Index" published by the Digital Finance Research Centre of Peking University as an indicator variable for the development of the digital economy (Xie et al., 2018). However, this index has a short time span and annual frequency, which is different from the sample of this paper, so other indicator variables must be found to measure the development of China's digital economy. The correlation between the "China Digital Financial Inclusion Development Index" and the "scale of third-party online payment" during the period of 2011-2015 was found. The correlation coefficient between the two was found to be 0.94, so the "scale of third-party online payment" can be considered as a proxy variable for the development of the digital economy.

4.2.2 Social Consumption (TSC/trillion Yuan)

In this paper, total retail sales of consumer goods are chosen to give a specific reflection of the volume of social consumption demand.

4.2.3 Economic Growth (GDP/trillion Yuan)

In this paper, GDP is chosen to represent economic growth.

The data for this paper are obtained from the National Bureau of Statistics, Econet Intelligence and Ariadne Consulting. The variables are selected as digital economic development, social consumption and economic growth respectively for econometric analysis. This paper uses quarterly data from 2015-2020 as the sample and performs a natural logarithm transformation on all raw data, with the transformed indicators being LNGDP, LNTSC, and LNIF respectively.

5. Empirical Analysis

5.1 Statistical Description

The statistical descriptions of the three variables (LNGDP, LNTSC, LNIF) are shown in Table 1.

Table 1. Statistical Description of the Variables

	LNGDP	LNTSC	LNIF
Mean	3.046044	2.18685	3.186848
Median	3.054001	2.200552	3.793239
Maximum	3.325036	2.442347	4.128746
Minimum	2.714695	1.95586	1.040277
Std. Dev.	0.166256	0.130908	1.083414
Skewness	-0.17369	-0.10783	-0.8824
Kurtosis	2.154397	2.260918	2.07776
Jarque-Bera	0.800891	0.568052	3.799826
Probability	0.670022	0.752747	0.149582
Sum	70.05901	50.29754	73.2975
Sum Sq. Dev.	0.608101	0.377012	25.82328
Observations	23	23	23

5.2 ADF Unit Root Test

In order to prevent the possibility of "pseudo-regression" of the selected data, a stationarity test was conducted on LNGDP, LNTSC and LNIF before building the VAR model. Table 2 shows the results of the ADF unit root test.

Table 2. ADF Unit Root Test Results

Variables	ADF	1%level	5% level	10%level	Differential orders	p	Stability
LNGDP	-7.508860	-4.467895	-3.644963	-3.261452	1	0.0000	Stable
LNTSC	-6.284848	-4.467895	-3.644963	-3.261452	1	0.0003	Stable
LNIF	-4.353848	-4.467895	-3.644963	-3.261452	1	0.0126	Stable

As can be seen from Table 1, LNGDP, LNTSC, and LNIF become smooth time series after first-order differencing, and all pass the ADF unit root test.

5.3 Determining the Optimal Lag of a VAR Model

In addition to conducting a smoothness test, determining the optimal lag of the VAR model is another step in building a VAR model that cannot be ignored. This step ensures that the model is tested at the optimal degree of freedom and increases the credibility of the results. The results are shown in Table 3.

Table 3. Results of Lag Order Judgement

Lag	LogL	LR	FPE	AIC	SC	HQ
0	38.35502	NA	3.95E-06	-3.928335	-3.77994	-3.907874
1	50.39039	18.72169	2.88E-06	-4.265599	-3.672018	-4.183752
2	63.34475	15.8331	2.07E-06	-4.704972	-3.666205	-4.56174
3	83.73969	18.12884*	7.83E-07	-5.971077	-4.487124	-5.76646
4	111.169	15.23849	2.07e-07*	-8.018775*	-6.089636*	-7.752773*

From the results of the analysis in Table 3, it can be concluded that with reference to the AIC and SC data, period 4 is the optimal lag period and a VAR model incorporating the development of the digital economy, social consumption and economic growth can be built.

5.4 Stability Check

The validity of the co-integration test and the impulse response and ANOVA results in the following section are provided by validating the AR roots to determine whether the model is stable, as shown in Figure 1 and Table 4.
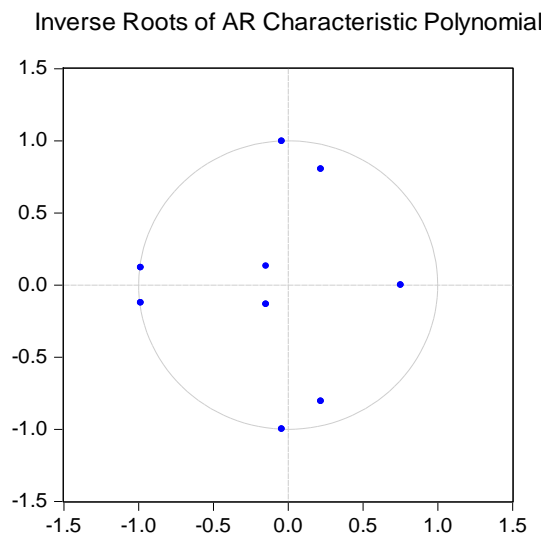
Figure 1. AR Root Test Results

Table 4. AR Root Test

Root	Modulus
-0.043172 - 0.997584i	0.998518
-0.043172 + 0.997584i	0.998518
-0.986057 - 0.122596i	0.993649
-0.986057 + 0.122596i	0.993649
0.218173 - 0.805529i	0.834552
0.218173 + 0.805529i	0.834552

0.752496	0.752496
-0.148417 - 0.132983i	0.199279
-0.148417 + 0.132983i	0.199279
No root lies outside the unit circle.	
The VAR satisfies the stability condition.	

From Figure 1 and Table 4, it can be seen that the inverse of all three variables meet the condition that the inverse is less than 1 and they are all distributed within the unit circle, indicating that the time series is smooth and the VAR model constructed in this study is stable and can be tested subsequently.

5.5 Co-integration Test

Using the Johansen co-integration test, it is possible to determine at a deeper level whether there is a long-term equilibrium relationship between the three variables, and the results of the co-integration relationship are shown in Table 5.

Table 5. Johansen Co-integration Test Results

HGDPpothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.958967	93.26271	29.79707	0
At most 1 *	0.762199	32.58855	15.49471	0.0001
At most 2 *	0.243358	5.298437	3.841466	0.0213

From Table 5, it can be seen that there are multiple co-integration relationships between the three economic relationships at the 5% significance level again, so it can be considered as a long-run dynamic equilibrium between the three.

5.6 Granger's Causality Test

To further test the causal relationship between the development of the national digital economy, social consumption and economic growth, this study used the Granger causality test. The results are shown in Table 6.

Table 6. Granger Causality Test

Null Hypothesis:	F-Statistic	Prob.	Conclusion
LNTSC does not Granger Cause LNGDP	4.13325	0.0563	Rejection
LNGDP does not Granger Cause LNTSC	6.55575	0.0191	Rejection
LNIF does not Granger Cause LNGDP	8.62714	0.0085	Rejection
LNGDP does not Granger Cause LNIF	0.0912	0.7659	No refusal
LNIF does not Granger Cause LNTSC	11.8161	0.0028	Rejection
LNTSC does not Granger Cause LNIF	0.51123	0.4833	No refusal

According to Table 6, at the 10% significance level, economic growth and social consumption contribute to each other, and the development of the digital economy is conducive to the increase in social consumption and economic growth. However, neither economic growth nor increase in social consumption are Granger causes of digital economy development.

5.7 Impulse Response Function

This study uses impulse response functions to analyse the long-term dynamic interactions between the three variables and to investigate the responses of different endogenous variables in the face of shocks to other variables as well as to themselves, in order to provide a deeper insight into the characteristics of the dynamic relationship between the three. The results are shown in Figure 2.
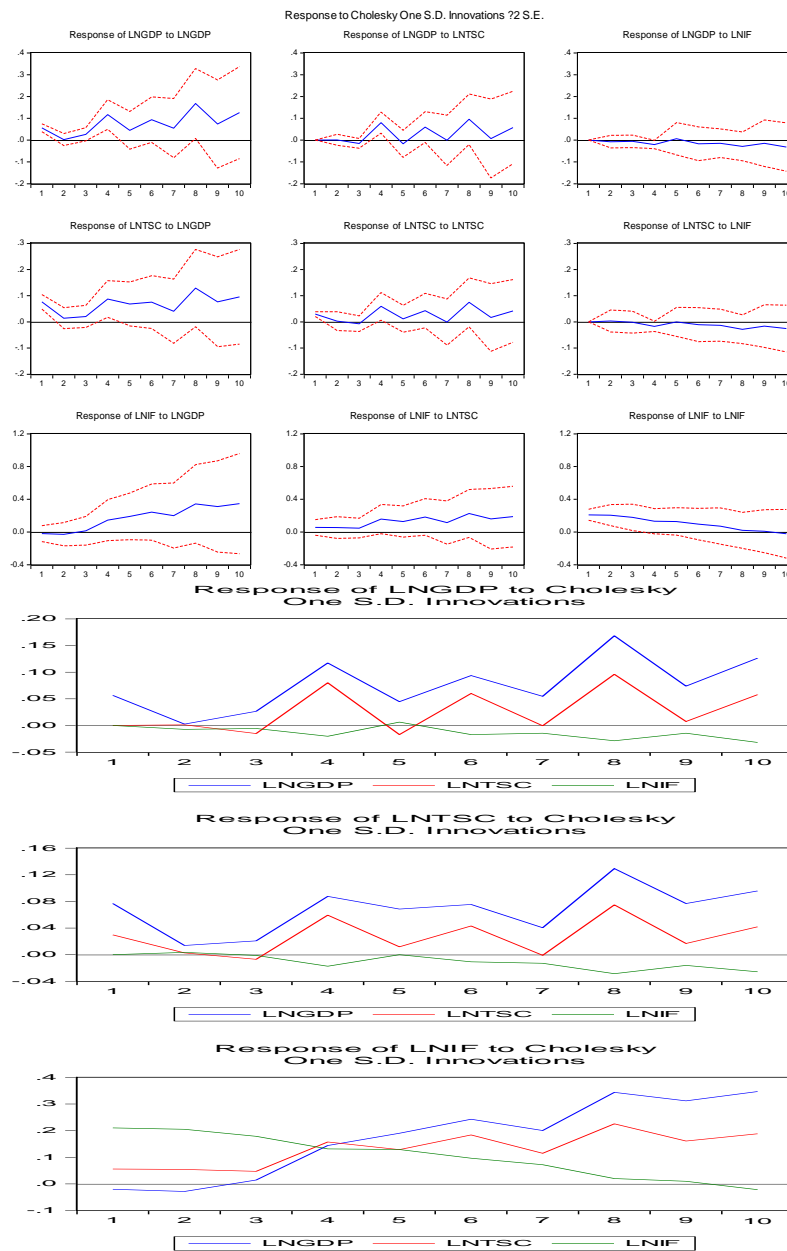

Figure 2. Impulse Response Function Curves for Each Variable

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5.7.1 Impulse Response Analysis of Economic Growth

When GDP is hit by a standard deviation shock in the period, it itself responds immediately from period 1, and it is an obvious positive response, and this positive response tends to fluctuate and strengthen after reaching its lowest value in period 2; both gross retail social consumption and digital economic development do not respond to economic growth shocks in period 1, and the response of digital economic development to economic growth shocks is negative, while The response of gross social retail sales to economic growth shocks is in the form of alternating positive and negative changes. This suggests that both digital economic development and social consumption shocks to economic growth have a time lag, and that in the long run, economic growth shocks have a negative effect on digital economic development and a more volatile effect on social consumption, with alternating positive and negative effects.

5.7.2 Impulse Response Analysis of Social Consumption

When total retail social consumption is hit by a standard deviation shock in this period, digital financial development has no response in period 1, a positive response in period 2, and a negative response from period 3 onwards; while in the long run, the response of GDP to social consumption shocks has been positive, showing a trend of fluctuating enhancement. This indicates that the impact of digital economy development on social consumption has a time lag, and in the long run, social consumption has a catalytic effect on economic growth and a consistent effect on digital financial development.

5.7.3 Analysis of the Interplay between Economic Growth and Digital Economy Development

When digital economic development is subjected to a standard deviation shock in this period, its own response reaches a maximum in period 1 and gradually tends to zero in the long run; the response of GDP is negative in periods 1-2 and reaches a minimum in period 2, from period 3 onwards the response is positive and increasingly obvious in the long run; the response of social consumption is positive in all periods and gradually obvious in the long run. This suggests that in the long run, the development of digital finance has a catalytic effect on both economic growth and social consumption.

5.8 Analysis of Variance Decomposition

In the VAR model, analysis of variance decomposition can be used to further assess the importance of different factors by using the contribution rates generated by shocks to each variable in the system's internal response. The results are shown in Table 7, Table 8 and Table 9.

Table 7. LNGDP ANOVA Results

Variance Decomposition of LNGDP:				
Period	S.E.	LNGDP	LNTSC	LNIF
1	0.056421	100	0	0
2	0.056966	98.28077	0.040754	1.678473
3	0.064922	92.40923	5.506247	2.084521

4	0.157501	71.16605	26.80879	2.025166
5	0.164715	72.40211	25.6039	1.993982
6	0.199473	71.43083	26.46772	2.101447
7	0.207339	73.05831	24.49869	2.442998
8	0.285194	73.39747	24.28431	2.31822
9	0.295011	74.83171	22.75646	2.411835
10	0.327624	75.53898	21.55469	2.906326

Table 8. LNTSC ANOVA Results

Variance Decomposition of LNTSC:

Period	S.E.	LNGDP	LNTSC	LNIF
1	0.082289	86.98312	13.01688	0
2	0.08355	87.11782	12.72013	0.162051
3	0.086384	87.27629	12.55492	0.168785
4	0.137523	74.82882	23.51618	1.655003
5	0.154027	79.36034	19.32029	1.319371
6	0.17714	78.10747	20.52633	1.366205
7	0.182165	78.7926	19.41288	1.794524
8	0.237199	76.11221	21.38291	2.504884
9	0.250378	77.69821	19.63565	2.666137
10	0.272505	77.92008	18.93899	3.140925

Table 9. LNIF ANOVA Model

Variance Decomposition of LNIF:

Period	S.E.	LNGDP	LNTSC	LNIF
1	0.21825	0.851122	6.506243	92.64263
2	0.305624	1.300271	6.432698	92.26703
3	0.357358	1.112388	6.450355	92.43726
4	0.436509	11.63963	17.33307	71.0273
5	0.509737	22.45015	19.07006	58.47979
6	0.601446	32.42834	23.00564	44.56602
7	0.648222	37.45611	22.94766	39.59623
8	0.767792	46.72149	24.988	28.29051
9	0.844174	52.28918	24.29514	23.41568
10	0.931982	56.73841	23.9961	19.26549

5.8.1 Analysis of Variance for Economic Growth

GDP explains a minimum of 71.17% of its own fluctuations, with 0-26.81% of fluctuations explained by social consumption and 0-2.9% of fluctuations explained by the development of the digital economy. Compared to the other variables, GDP itself contributes 100% in period 1, showing a general downward trend in fluctuations, but still being the main explanatory contributor. In contrast, the response of both digital economic development and social consumption is zero in period 1, indicating a time lag in the response of both to economic growth shocks, with the impact of economic growth on social consumption being greatest in period 2 and slowly weakening in the long run, while the impact of economic growth on digital economic development gradually increases in the long run. Overall, both have a time lag in their response to economic growth shocks, which are more pronounced for social consumption relative to digital economic development, but increasingly so in the long run.

5.8.2 Analysis of Variance for Total Retail Sales of Social Consumption

GDP explains up to 87.3% of the fluctuations in social consumption, while digital economic development explains 0-3.14 of the fluctuations and itself explains up to 23.5 of the fluctuations. Compared with other variables, the response of digital economic development in period 1 is 0, indicating that the response of digital economic development to social consumption shocks has a time lag, but in the long term in, its response is all positive and gradually increasing; GDP has the largest response in period 1, and in the long term in the response is all positive but the response gradually weakening, but still accounts for a large proportion overall. In general, the response of digital economy development to social consumption shocks is slow with time lag and takes a long time to become significant, reflecting the long-term accumulative nature.

5.8.3 Analysis of Variance for Digital Economy Development

The response of economic growth to shocks from the digital economy is positive but increases in the long term; the response of social consumption to shocks from the digital economy is positive and tends to fluctuate and increase.

In summary, there is no good circular mechanism between the three.

6. Conclusions and Recommendations for Countermeasures

6.1 Conclusion

6.1.1 Digital Economy Development and Social Consumption for Economic Growth

Both social consumption and digital economic development contribute to economic growth, but in relative terms the contribution of social consumption is more pronounced and digital economic development is more significant in the long run, but both have a time lag in their contribution to economic growth. This suggests that social consumption and digital economic development are important influences on economic growth, with higher levels of digital finance and increasing digital economic development injecting a constant and powerful driver of economic growth, which, on the other hand, also validates the increase in social efficiency from digital economic development, which is

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a cumulative process over time. Social consumption makes a significant contribution to boosting economic growth, reflecting the fact that the more buoyant the economic market, the faster the economic growth. The retail sector of goods and restaurant revenues are also important factors influencing economic growth, indirectly reflecting people's expectations of material and cultural living standards over a certain period of time.

6.1.2 Economic Growth and the Development of the Digital Economy as a Catalyst for Social Consumption

Both economic growth and the development of the digital economy have a catalytic effect on social consumption. Among them, the promotion of economic growth is obvious and the economic growth and social consumption form a good dynamic cycle.

6.1.3 There is no Good Dynamic Cycle between Economic Growth, Social Consumption and the Development of the Digital Economy

The main manifestation is that the response to the development of the digital economy under the impact of economic growth and social consumption is weak and remains insignificant in the long term. This suggests that the benefits from economic growth and social consumption have not been fully expressed and that further development is needed in terms of innovation drivers.

6.2 Suggestions for Countermeasures

The empirical analysis leads to the conclusion that there is a time lag between economic growth, the development of the digital economy and social consumption, with a medium-term relationship, but that the three do not constitute a good cycle.

6.2.1 Strengthen Digital Economy Development, Increase Investment in Digital Economy Development and Improve Output Efficiency

The role of the digital economy in driving economic growth and social consumption should be fully appreciated, so investment in the development of the digital economy should be increased as well as the audience for the development of the digital economy, with constant attention to its output efficiency.

6.2.2 Stimulating the Innovation Drive and Strengthening the Pull to the Development of the Digital Economy

Although economic growth and social consumption form a good cycle, the development of the digital economy has not formed a good dynamic cycle with any of the variables, and since this is a long-term cumulative process, a variety of socially beneficial policies should be introduced to stimulate the development of the digital economy in terms of innovation drives and various types of finance, credit and investment.

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