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Research article

The impact of digital economy on the financial risk ripple effect: evidence from China

Zimei Huang[1] and Zhenghui Li[1,2,*]

[1] School of Economics and Statistics, Guangzhou University, Guangzhou 510006, China
[2] Guangzhou Institute of International Finance, Guangzhou University, Guangzhou 510006, China

* **Correspondence:** Email: lizh@gzhu.edu.cn.

Abstract: The impact of the digital economy on the ripple effect of financial risks has attracted attention. Based on the data of flow of funds statements (financial accounts), spanning from 2011 to 2020, the fund flow analysis method was used to build a model measuring financial risk ripple effect. Second, we built a panel regression model, which studies the impact of the digital economy on the ripple effect of financial risks. In addition, we explored the heterogeneous effects of different dimensions of the digital economy on the ripple effect of financial risks. Our findings revealed several key conclusions. First, the total financial risk ripple effects between 2011 and 2020 continued to change, and the ripple effects of different types of financial risks have heterogeneity. Second, the digital economy has a negative impact on the ripple effect of financial risks. Third, the different dimensions of the digital economy have heterogeneity in the ripple effect of financial risks. Specifically, the digital economy user index and the digital economy innovation index have a negative impact on financial risk ripple effect. The digital economy platform index and the digital economy industry index have insignificant effects on financial risk ripple effect.

Keywords: digital economy; financial risk ripple effect; fund flow analysis method
Mathematics Subject Classification: 62P20

1. Introduction

The digital economy, as a new socio-economic form, has become an important driving force for economic growth in various countries and has greatly changed people's lifestyles. The digital economy is based on data resources as the key element, with modern information networks as the main carrier, and information communication technology integration applications. The digital transformation of the total factor is an important driving force to promote a new economic form with fairness and efficiency [1–3], promote the development of industrial integration with digital technology, and accelerate the digital transformation of the financial sector. First of all, the digital economy helps to promote the deepening application of big data, artificial intelligence, blockchain, and other technologies in the fields of banking, securities, insurance, and other fields; develop new models such as smart payment, smart outlets, smart investment, digital financing, etc.; and promote digital RMB research and development. Second, the digital economy can expand diversified investment and financing channels to help enterprises carry out technological innovation [4–7]. At the same time, digital economy enterprise financing through equity investment and stock bond issuance will help increase the proportion of direct financing and improve the financing structure. It can be seen that with the help of digital technologies such as big data and cloud computing, financial institutions can deeply explore the internal and external information of enterprises, strengthen financial institutions' perception and response capabilities for corporate risk changes, improve the accuracy of risk assessment, strengthen the comprehensive research and judgment of digital economic security risks, prevent various types of risks overlapping economic risks, technical risks, and social stability issues, and reduce the ripple effects of financial asset risks. Therefore, clarifying the influence of the digital economy on the ripple effect of financial risks is of great practical significance.

With global economic integration and financial liberalization, financial crises occur frequently and spread widely, and the frequency and intensity are on the rise, which brings severe challenges to the economy and society. For large economies, China believes that finance is the blood of the real economy. Actively preventing and defusing financial risks and holding the bottom line of no systemic financial risks is an inevitable requirement for China to build a modern economic system and achieve high-quality development. On October 31, 2023, the Central Financial Work Conference pointed out that "finance is the blood of the national economy and an important part of the country's core competitiveness. It is necessary to accelerate the construction of a financial power, comprehensively strengthen financial supervision, improve the financial system, optimize financial services, and prevent and defuse risks". It can be seen that the Chinese government is extremely concerned about the spillover effect of financial risks. Therefore, this paper measures the ripple effect of financial risks in China based on China's flow of funds data and explores the impact of the digital economy on the ripple effect of financial risks in China.

At present, research on the influence of the digital economy mainly includes three aspects: the impact of the digital economy on high-quality development, the impact of the digital economy on the real economy, and the impact of the digital economy on finance.

First, the digital economy promotes high-quality development. The digital economy has significantly promoted high-quality economic development through economic efficiency improvement and economic structure optimization. At the micro level, the network effect of digital technology not only helps enterprises to realize economies of scale and economies of scope in production but also helps to improve innovation ability and allocative efficiency. Li et al. [8] explored the changes in corporate financing constraints brought about by the digital economy and its impact on corporate innovation, based on the data of 3328 A-share listed firms in China for the period from 2011 to 2021. They found that the impact of the digital economy on corporate innovation is positive and significant, and financial constraints act as a transmission mechanism through which the digital economy promotes corporate innovation. Hunjra et al. [9] found that China's big data comprehensive pilot zones (BDCPZ) policy facilitated corporate low-carbon innovation, especially for state-owned enterprises, low-technology firms, and firms with highly educated CEOs. At the level of the middle view, digital economy accelerates industrial structure adjustment, optimization, transformation and upgrading and improves industrial quality through industrial innovation effects, industrial correlation effects, and industrial convergence effects [10,11]. For example, Xiong et al. [12] used panel data from 31 jurisdictions in China to find that the digital economy promotes the modernization of industrial structure by influencing the rationalization and upgrading of industrial structure through the technical level and factor level. Liu [13] explored the effects of the digital economy on industrial eco-efficiency. Their results indicated that digital economy has a significantly positive effect on industrial eco-efficiency. At the macro level, digital economy can not only promote economic growth through enrichment of the source of factors and improve the element allocation efficiency and capital deepening effects but also improve the total factor productivity and promote high-quality economic development through technological innovation and diffusion effects [14]. Pan et al. [15] examined the innovation-driven effects of the digital economy on total factor productivity (TFP) in China. They found that the digital economy index has a positively nonlinear relationship with provincial TFP, and it demonstrates that the digital economy acts as an innovation driver for the extensive and sustainable development of TFP. Guo et al. [16] employed a difference-in-differences approach to find that the digital economy significantly stimulates high-quality economic development through two mechanisms: improving human capital and promoting green technology innovation.

The digital economy promotes the development of the real economy. The digital economy has a dual effect on the real economy, and the promotion effect is significantly stronger than the inhibitory effect. On the one hand, the digital economy has a positive impact on the real economy. The digital economy has indirectly promoted the development of the real economy through technological innovation and foreign investment. Digital industrialization has significantly promoted the improvement of the total factor productivity of industrial enterprises, promoting the development of the real economy. The development of digital industrialization can indirectly promote the development of the real economy by strengthening the internal control and cost management of enterprises. Digital technologies such as big data, industrial internet, and artificial intelligence can promote industrial digital transformation [17], enhance the competitive advantage of enterprise, enhance the modernization level and independent controllable capabilities of the industrial chain, and improve the international competitiveness of industry. Wu and Yang [18] analyzed the impact of the development of the digital economy on China's employment structure, and they found that digital economy has significantly impacted China's employment structure. Sun et al. [19] empirically tested the impact of the integration of the digital economy and real economy on enterprise green innovation, and they found that integrating the digital economy and the real economy significantly positively affects green innovation. On the other hand, the digital economy has a negative impact on the real economy. The digital economy has an inhibitory effect on the real economy by affecting the development of traditional financial development. Liu [20] used panel data from 31 Chinese provinces covering the years 2011–2020 to investigate the long-term equilibrium between digital finance and the real economy. They found that in the long run, digital finance exhibits a noticeable inhibiting effect on the real economy.

The digital economy has an impact on finance. First of all, digital technology promotes the transformation of traditional financial institutions' business model, and financial institutions can provide differentiated financial services by using digital technology [21–27]. Ahmad et al. [28] believed that rapid expansion of digital financial inclusion in the last few years has dramatically augmented the accessibility and affordability of financial services and positively contributes to higher economic growth. Besides that, digital technology helps improve the operating efficiency of financial institutions and reduce operating costs. The development of digital technology helps improve service efficiency of financial institutions, improve payment efficiency, promote changes in the concept of regulatory supervision, and help improve the efficiency of regulatory supervision. In addition, the application of digital technology helps real economy of financial services to effectively alleviate the problems of difficulty, weak capabilities, and high cost and then improve the level of financial services.

The above research provides a wealth of literature and also leaves further research space for this article. The impact of the digital economy and its different dimensions on financial risk ripple effects are worth further discussion.

This paper aims to examine the impact of the digital economy on the ripple effect of financial risks in China for the period 2011–2020. First, we calculate the ripple effect of financial risks in China. Based on the flow of funds statement (financial accounts) data of China spanning from 2011 to 2020, using a fund flow analysis method, this article uses the Leontief inverse matrix to build a model measuring financial risk ripple effects, and the results show that the total financial risk ripple effects from 2011–2020 are constantly changing, and the financial risk ripple effects of different types have heterogeneity. Second, we explore the impact of the digital economy on financial risk ripple effects. Based on the data from 2011 to 2020, this article found that the digital economy has a negative impact on financial risk ripple effects. Third, we explore the impact of different dimensions of the digital economy on the effect of financial risk ripple effects. The results show that the digital economy of different dimensions exerts heterogeneous impacts on the financial risk ripple effects. Specifically, the digital economy user index and the digital economy innovation index have a negative impact on financial risk ripple effects. The digital economy platform index and the digital economy industry index have insignificant effects on financial risk ripple effects.

Compared to previous studies, the contribution of this article mainly includes the following three aspects. First, we measure the ripple effects of financial risks in China by using a fund flow analysis method and analyze the evolutionary characteristics of ripple effects of financial risk. Second, this article studies the impact of the digital economy on financial risk ripple effects in China from a macro perspective. The existing literature mainly studies the impact of the digital economy on high-quality development, the real economy, finance, and other aspects, and it has not yet studied the impact of the digital economy on financial risk spillover effect from a macro perspective. Third, this article explores the impact of different dimensions of the digital economy on the effect of financial risk ripple effects. The study of the impact of different dimensions of the digital economy on the financial risk ripple effects helps one to clearly understand the difference of each dimension on financial risk ripple effects.

The remainder of the paper is organized as follows. Section 2 mainly measures the financial risk ripple effects and analyzes their characteristics. Section 3 describes the method, variable selection and data sources used in our empirical analysis. And the empirical results are presented in Section 4. Section 5 is conclusion.

2. Measurement of financial risk ripple effects

This section mainly measures the ripple effects of financial risks. Section 2.1 mainly introduces the measured steps of financial risk ripple effects. Section 2.2 mainly analyzes the measurement results of the financial risk ripple effect.

2.1. The measurement steps of financial risk ripple effects

This paper uses financial account data to measure financial risk ripple effects. The flow of funds statement (financial accounts) compiled by the People's Bank of China describes the flows and shortages of funds between various institutional sectors, which can reflect the scales and structures of financial transactions in economic activities, and the financial debt relationships between institutional sectors. Based on the flow of funds statement (financial accounts) data from 2011–2020, this paper measures the financial risk ripple effect between institutional sectors. The data of the flow of funds statement (financial accounts) from 2011–2020 comes from the official website of the People's Bank of China.

Referring to Zhang Nan [29], this article uses the flow of funds statement (financial accounts) data to measure the ripple effects of financial risks. It mainly includes five steps.

First, the flow of funds statement is split into the funds source table R and the fund use table E. In the flow of funds statement, the rows represent various types of financial transactions, and the columns represent the sources and uses of funds in the institutional sector (non-financial corporations, financial institutions, general government, households, and the rest of the world). According to the double entry accounting method, the sources and uses of funds of the five institutional sectors are separated, and the source of funds (R) and use of funds (E) of each financial transaction item of each institutional sectors are established.

Second, the source and use of funds are treated negatively. In order to obtain the proportion coefficient of the positive number, the negative number needs to be converted into a positive number. Therefore, the negative numbers in the fund use table is adjusted, and the negative number of the liability party in the flow of funds statement will be transformed into positive numbers and moved to the corresponding asset party to obtain the positive flow of funds. The adjusted statement of the source of funds and the statement of the use of funds still comply with the principle of double-entry accounting. According to the above methods, the fund source and fund use tables of 2011–2020 are processed.

Then, the from-whom-to-whom tables are compiled. According to the fund source table and fund use table, it is assumed that the financial instruments of various institutional sectors will raise funds at the same ratio to compile from-whom-to-whom tables. Financial assets and liabilities and corresponding fund flow directions and scales are calculated as follows:

$$\text{Debt ratio coefficient} = \text{Financial liabilities held by the sector} / \text{total financial liabilities} \tag{1}$$

$$\begin{aligned}&\text{The amount of financial assets held by the asset side sector}\\&\quad = \text{Debt ratio coefficient} * \text{the financial assets held by the sector}\end{aligned} \tag{2}$$

According to Eqs (1) and (2), the debt ratio coefficient is first calculated. Second, the liability coefficient matrix B and the asset coefficient matrix D are calculated according to the fund source table R and the fund use table E. Divide each financial instrument in Table R by the sum of the assets or liabilities t_j of each institutional sector to obtain the liability coefficient matrix B. The calculation of each coefficient in the liability coefficient matrix B is shown in Eq (3):

$$b_{ij} = \frac{r_{ij}}{t_j}. \tag{3}$$

In the same way, the elements of the transpose matrix $\boldsymbol{E'}$ of table E are divided by the sum of rows t_i^E to obtain the asset coefficient matrix D. The calculation of each coefficient in the asset coefficient matrix D is shown in Eq (4):

$$d_{ji} = \frac{e_{ji}}{t_i^E}. \tag{4}$$

Finally, a ripple effect model of financial risk is constructed to calculate the ripple effect of financial risk. When financial assets of a sector are lost due to default, the loss of assets affects all liabilities in proportion to the five institutional sectors: households, non-financial corporations, general government, financial institutions, and the rest of the world. The loss caused by the default of one institutional sector is called the direct ripple effect. Due to the direct ripple effect, the assets of the institutional sector shrink and become insolvent, resulting in a decrease in the value of the institutional sector. Due to the chain reaction, the affected sector will default on other institutional sectors, resulting in the loss of assets of other institutional sectors, which is called the first indirect ripple effect. These negative effects spread rapidly to other institutional sectors through the lending relationship between institutional sectors and then result in the second indirect ripple effect, the third indirect ripple effect, and so on.

Assuming that the default amount is -s, the default risk of -s will gradually trigger a chain ripple effect through the fund and credit relationship between institutions sectors and may eventually produce a credit crisis in the whole society.

Suppose that a financial instrument defaults on 1 unit amount, and no other financial instrument defaults. Then, *s*(financial instrument)=-1, i.e., $s = (0, \cdots, 0, -1, 0, \cdots 0)'$. The matrix $\boldsymbol{Z_0}$ represents the direct losses that will be suffered by each institutional sector, which can be expressed as

$$\boldsymbol{Z_0} = \boldsymbol{D}s. \tag{5}$$

In Eq (5), D is the asset coefficient matrix.

Sectors that are directly affected raise funds through the combination of various funding sources. When there is no way to inject funds, a default proportional to all liabilities can occur. By multiplying the direct ripple effect matrix $\boldsymbol{Z_0}$ by the liability coefficient matrix B, the loss of the direct ripple effect is calculated according to the use of different funds. By multiplying the loss of the direct ripple effect by the asset coefficient matrix D, the indirect ripple loss of each institutional sector is calculated, which is called the indirect primary ripple effect, which is expressed by the matrix $\boldsymbol{Z_1}$. Then, the indirect primary ripple effect $\boldsymbol{Z_1}$ can be expressed as

$$\boldsymbol{Z_1} = \boldsymbol{DBZ_0}. \tag{6}$$

The negative impact of the previous stage will be transmitted to the next stage according to the ratio of the inter-institutional sector funding correlation matrix DB. By analogy, the indirect second ripple effect $\boldsymbol{Z_2}$ can be expressed as

$$\boldsymbol{Z_2} = \boldsymbol{DBZ_1} = (\boldsymbol{DB})^2\boldsymbol{Z_0}. \tag{7}$$

The indirect third ripple effect $\boldsymbol{Z_3}$ can be expressed as

$$Z_3 = DBZ_2 = (DB)^3 Z_0. \tag{8}$$

The indirect k-order ripple effect Z_k can be expressed as

$$Z_k = DBZ_{k-1} = (DB)^k Z_0. \tag{9}$$

The sum of the direct ripple effect to the indirect k th ripple effect $\mathcal{E}_k$ can be expressed as

$$\begin{aligned}\mathcal{E}_k &= Z_0 + Z_1 + Z_2 + \cdots + Z_k \\ &= Z_0 + DBZ_0 + (DB)^2 Z_0 + \cdots + (DB)^k Z_0.\end{aligned} \tag{10}$$

When $k \to \infty$, $\mathcal{E}_\infty$ denotes the sum of the direct ripple effect and the indirect ripple effect from 1 to infinity when a default occurs in an institutional sector, which can be expressed as

$$\mathcal{E}_\infty = (I - DB)^{-1} Z_0. \tag{11}$$

To sum up, when only a financial instrument defaults on 1 unit of amount, and other financial instruments do not, according to Eqs (5)–(8) and (11), the direct ripple effect Z_0, indirect primary ripple effect Z_1, indirect second ripple effect Z_2, indirect third ripple effect Z_3, and the sum of direct and indirect ripple effects $\mathcal{E}_\infty$ are calculated.

2.2. Analysis of the measurement results of the financial risk effect

Based on different financing methods, this article divides 29 financial instruments into three categories: domestic direct financing, domestic indirect financing, and foreign financing. Specifically, domestic direct financing mainly includes six financial instruments such as share, financial bonds, corporate bonds, investment funds, government and public bonds, and central bank bonds. Domestic indirect financing covers 19 financial instruments, including insurance technical reserves, fiscal deposit, required and excessive reserves, time deposit, short-term loan and discounted commercial paper loan, demand deposit, inter-financial institutions accounts, cash in vault, miscellaneous (net), other deposit, other loans, currency, foreign exchange deposit, foreign exchange loans, designated loans, not discounted banker's acceptance bills, customer margin of securities company, central bank loans, and medium-term and long-term loans. Foreign financing includes four financial instruments: changes in reserve assets, errors and omissions in the BOP, changes in other foreign assets and debts, and foreign direct investment. According to the classification of three kinds of financial instruments, this paper measures the risk ripple effects of three kinds of financing methods and the total financial risk ripple effect. The calculation results of the financial risk ripple effects of 2011–2020 are shown in Table 1.

The total ripple effect of financial risks during the period from 2011 to 2020 exhibits dynamic changes, with heterogeneous ripple effects observed across different risk types. As depicted in Table 1, on one hand, the total ripple effect of financial risks during the period from 2011 to 2020 displays a fluctuating pattern and can be divided into three stages. From 2011 to 2016, there was an upward trend in the ripple effect of financial risks, reaching its peak value of 50.57 in 2016. Subsequently, from 2016 to 2018, a brief downward trend was witnessed in the ripple effect of financial risks, hitting its lowest point at 9.94 in 2018. Finally, from 2018 to 2020, the ripple effect of financial risks continued rising and reached 16.44 in 2020. On the other hand, different types of risk ripple effects exhibit heterogeneity. As evidence from Table 1, the ripple effect of financial risks for foreign financing is greater than that for domestic direct financing and domestic indirect financing projects. Moreover, the ripple effect of financial risks for domestic direct financing is larger than that for domestic indirect financing.

Table 1. Financial risk ripple effect from 2011 to 2020.

Year	Domestic indirect financing risk ripple effects	Domestic direct financing risk ripple effects	Foreign financing risk ripple effects	Total financial risk ripple effects
2011	5.92	6.42	7.33	19.67
2012	5.84	6.27	7.25	19.36
2013	7.61	8.21	9.07	24.89
2014	7.46	7.83	8.81	24.10
2015	6.78	7.40	7.92	22.11
2016	16.12	17.02	17.43	50.57
2017	10.44	11.23	11.54	33.21
2018	2.85	3.00	4.09	9.94
2019	3.33	4.04	4.57	11.94
2020	4.78	5.54	6.12	16.44

3. Model and data sources

This section mainly introduces the panel regression model. Section 3.1 mainly introduces the panel regression model. Section 3.2 briefly describes variables selection and data sources. Section 3.3 is descriptive statistical analysis of variables.

3.1. Panel regression model

To investigate the impact of the digital economy on the financial risk ripple effect, we specify the panel regression model. Panel regression models are estimated through employing recently developed techniques like mean group estimators, which allow for heterogeneity in the estimation of the slope coefficients. The major advantage of using panel regression model is that this model encompasses data across cross sections and over time series [30], thus providing a comprehensive analysis to examine the influence of the digital economy on the financial risk ripple effect. Since the explained variable is the financial risk ripple effect, and the explanatory variable is the digital economy index of 30 provinces and cities, this paper adopts the panel regression model to empirically analyze the impact of the digital economy on the financial risk ripple effect according to the panel data characteristics. Besides that, it can provide more efficient estimation and information of the impact of the digital economy on the financial risk ripple effect. The baseline panel regression model is as Eq (12).

$$Total_{it} = \beta_0 + \beta_1 * DEI_{it} + \beta_2 * EDU_{it} + \beta_3 * PCC_{it} + \beta_4 * CS_{it}$$
$$+\beta_5 * SD_{it} + \beta_6 * PAY_{it} + \beta_7 * INS_{it} + \beta_8 * CL_{it} + \varepsilon_{it}. \quad (12)$$

where the subscript it indicates province i in time period t. $Total$ represents the total financial risk ripple effect, DEI refers to digital economy index, EDU denotes the average number of students enrolled in colleges and universities per 100,000 population, PCC is per capita consumption expenditure of all residents, and CS refers to coverage breadth of digital finance. SD represents use depth of digital finance. PAY refers to payment usage index. INS is insurance usage index, and CL is the credit usage index. β denotes the vectors of estimated parameters in the equation, β_1 indicates the impact of digital economy on financial risk ripple effect. ε_{it} is the error term. In the baseline panel regression model, we have not conditioned the impact of digital economy on financial risk ripple effect. Therefore, the coefficients in the baseline panel regression model show the unconditional impacts of the digital economy on the financial risk ripple effect.

To further investigate the heterogeneous impact of different dimensions of the digital economy on the financial risk ripple effect, we replace the digital economy index with four digital economy sub-indexes. The digital economy sub-indexes include the digital economy platform index (PDEP), digital economy user index (PDEU), digital economy innovation index (PDEIN), and digital economy industry index (PDEI).

3.2. Variables selection and data source

The explained variable of the panel regression model is total financial risk ripple effect. In the second section, we measured the total financial risk ripple effect and three types of financial risk ripple effects according to the way of financing, including domestic direct financing financial risk ripple effect, domestic indirect financing financial risk ripple effect, and foreign financing financial risk ripple effect. The data measuring the financial risk ripple effect is from the flow of funds statement (financial accounts) compiled by the People's Bank of China.

The explanatory variables in our study are digital economy index (DEI), digital economy users index, digital economy platforms index, digital economy industry index, and digital economy innovation index. The existing literature on measuring digital economy index mainly measures the digital economy from national, provincial [31], and city [32, 33] perspectives. Referring to Xu and Li [31], we adopt a combination of entropy weighting method and grey target theory and select four dimensions, including digital users, digital platforms, digital industries, and digital innovation, to construct the digital economy index. Besides that, we further investigate the heterogeneous impact of these four dimensions of digital economy on financial risk ripple effect. The data is from the National Bureau of Statistics and Express Professional Superior (EPS) Database.

Moreover, to avoid an omitted variable bias, several important control variables are introduced in our panel data model. Control variables added to the model include seven ones: average number of students enrolled in colleges and universities per 100,000 population (EDU), per capita consumption expenditure of all residents (PCC), coverage breadth of digital finance (CS), use depth of digital finance (SD), payment usage index (PAY), insurance usage index (INS), and credit usage index (CL). The data is from the National Bureau of Statistics and Institute of Digital Finance of Peking University.

The measurement and sources of the above variables are as Table 2. The sample period in our study is based on the availability of annual data, spanning the period 2011–2020. The data sources of variables are described in Table 2.

Table 2. Variables and data sources.

Variable	Variable name	Variable abbreviation	Data source
Explained variable	Total financial risk ripple effect	Total	People's Bank of China
	Domestic direct financing risk ripple effects	DDF	People's Bank of China
	Domestic indirect financing risk ripple effects	DIF	People's Bank of China
	Foreign financing risk ripple effects	FF	People's Bank of China
Explanatory variable	Digital economy index	DEI	Xu and Li [16]
	Digital economy platform index	PDEP	Xu and Li [16]
	Digital economy user index	PDEU	Xu and Li [16]
	Digital economy innovation index	PDEIN	Xu and Li [16]
	Digital economy industry index	PDEI	Xu and Li [16]
Control variable	Average number of students enrolled in colleges and universities per 100,000 population	EDU	National Bureau of Statistics
	Per capita consumption expenditure of all residents	PCC	National Bureau of Statistics
	Coverage breadth of digital finance	CS	Institute of Digital Finance, Peking University
	Use depth of digital finance	SD	Institute of Digital Finance, Peking University
	Payment usage index	PAY	Institute of Digital Finance, Peking University
	Insurance usage index	INS	Institute of Digital Finance, Peking University
	Credit usage index	CL	Institute of Digital Finance, Peking University

3.3. Descriptive statistics

Table 3 summarizes descriptive statistics for all variables used in our study. Descriptive statistics are presented to describe the basic characteristics of data in this study spanning from 2011–2020. For each variable, we present the observation (N), mean (Mean), standard deviation (SD), minimum (Min), and maximum (Max), respectively. It can be seen that the maximum value of total financial risk ripple effect is 50.57, the minimum value is 9.94, and the mean is 23.223, indicating that total financial risk ripple effect is large and varies significantly from 2011 to 2020. The means of domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects are 7.696, 7.113, and 8.413, and the maximum values are 17.02, 16.12, and 17.43, respectively. These numbers reveal that the ripple effects of different types of financial risks are different. Besides that, the digital economy index ranges from 1 to 2.729, and the standard deviation is 0.242.

Table 3. Descriptive statistics.

Variables	N	Mean	SD	Min	Max
DEI	310	1.285	0.242	1	2.729
PDEP	310	1.561	0.309	0.000	2.377
PDEU	310	1.456	0.229	0.000	2.132
PDEIN	310	1.405	0.353	0.000	2.998
PDEI	310	1.549	0.333	1.000	2.780
EDU	310	2.608	0.812	1.082	5.613
PCC	310	16.512	7.151	5.063	45.605
CS	310	1.967	0.966	0.02	3.97
SD	310	2.111	0.982	0.068	4.887
PAY	310	1.848	0.918	0	3.795
INS	310	4.697	2.16	0.003	9.454
CL	310	1.382	0.632	0.012	2.96
Total	310	23.223	11.107	9.94	50.57
DDF	310	7.696	3.795	3	17.02
DIF	310	7.113	3.662	2.85	16.12
FF	310	8.413	3.655	4.09	17.43

Note: N, Mean, SD, Min, and Max are observations, mean, standard deviation, minimum and maximum, respectively. The data set covers 10 years from 2011 to 2020.

4. Empirical analysis of the impact of the digital economy on financial risk ripple effect

This section mainly analyzes the impact of the digital economy on financial risk ripple effect. Section 4.1 shows the empirical results of the impact of digital economy on financial risk ripple effect. Section 4.2 mainly explores the heterogeneous impact of different dimensions of digital economy on the ripple effects of financial risks.

4.1. Impact of digital economy on financial risk ripple effect

First, we examine the impact of the digital economy on the financial risk ripple effect. So as to minimize the endogeneity problem caused by the omission of explanatory variables, this paper added seven control variables and controlled for time fixed effects and industry fixed effects. Table 4 presents the panel regression results of the impact of the digital economy on financial risk ripple effect in the period 2011–2020. Columns (1) to (4) in Table 4 present the impacts of the digital economy on total financial risk ripple effect, domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects, respectively.

The digital economy had a significantly negative impact on financial risk ripple effect. From Column (1) of Table 4, we can know that the coefficient of DEI is -29.548, which is significantly negative at the 1% statistical level. This suggests that when the digital economy index is higher, total financial risk ripple effect will be reduced. From the economic point of view, on average, an increase of one standard deviation (0.242) in digital economy index leads to a decrease of total financial risk ripple effect equivalent to 64.38% (=-29.548*0.242/11.107) of the sample standard deviation. It can be seen that both statistically and economically, the digital economy has a significant negative relationship with total financial risk ripple effect. Then, we divide the total financial risk ripple effect into domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects. In Columns (2) to (4), the coefficients of DEI are -10.137, -9.697 and -9.719, which are statistically significant at the 1% level. This suggests that when the digital economy index is higher, the domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects will be reduced. From what has been discussed above, the financial risk ripple effect, whether total financial risk ripple effect or domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects, can reduce when the digital economy index improved. This phenomenon may be due to the development of the digital economy, which has injected vitality into the financial sector, strengthened and improved the financial supervision mechanism, guaranteed the stable development of the financial sector, and thus reduced the ripple effect of financial risks among institutions.

Table 4. The impact of DEI on Financial risk ripple effect.

	(1) Total	(2) DDF	(3) DIF	(4) FF
DEI	-29.548***	-10.137***	-9.697***	-9.719***
	(-4.08)	(-4.02)	(-4.10)	(-4.11)
EDU	10.757***	3.809***	3.403***	3.547***
	(3.20)	(3.30)	(3.10)	(3.21)
PCC	-1.487***	-0.500***	-0.501***	-0.485***
	(-2.87)	(-2.78)	(-2.97)	(-2.87)
CS	-50.006***	-17.230***	-16.372***	-16.408***
	(-12.35)	(-12.42)	(-12.37)	(-12.22)
SD	-10.106***	-3.429***	-3.330***	-3.339***
	(-2.75)	(-2.73)	(-2.76)	(-2.75)
PAY	41.726***	14.307***	13.810***	13.608***
	(14.27)	(14.37)	(14.42)	(14.00)
INS	7.917***	2.692***	2.601***	2.624***
	(6.62)	(6.58)	(6.64)	(6.64)
CL	17.653***	6.253***	5.676***	5.718***
	(3.36)	(3.47)	(3.30)	(3.31)
_cons	38.658***	12.437***	12.612***	13.604***
	(4.64)	(4.33)	(4.62)	(4.99)
N	310	310	310	310
R^2	0.615	0.610	0.620	0.615
adj. R^2	0.561	0.555	0.567	0.561

Note: (1) Dependent variable Total is defined as total financial risk ripple effect, while the DDF, DIF, FF are domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects, respectively. The independent variable DEI is digital economy index. (2) The data set covers from 2011 to 2020. (3) t statistics are in parentheses. (4) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. (5) All variables are defined in Table 2.

4.2. Heterogeneous influence of digital economy sub-index on financial risk ripple effect

Then, so as to examine the heterogeneous impact of the digital economy sub-index on financial risk ripple effect, this paper uses the digital economy sub-index, including digital economy users index, digital economy platforms index, digital economy industries index and digital economy innovation index, to conduct the heterogeneous impact. Tables 5–8 presents the results of impact of heterogeneous digital economy sub-index on financial risk ripple effect in the period 2011–2020.

Table 5. The impact of PDEP on Financial risk ripple effect.

	(1) Total	(2) DDF	(3) DIF	(4) FF
PDEP	-6.040	-1.980	-2.037	-2.026
	(-1.15)	(-1.09)	(-1.18)	(-1.18)
EDU	7.834**	2.796**	2.450**	2.590**
	(2.45)	(2.55)	(2.34)	(2.46)
PCC	-2.765***	-0.938***	-0.920***	-0.906***
	(-6.96)	(-6.83)	(-7.07)	(-6.97)
CS	-45.977***	-15.845***	-15.051***	-15.084***
	(-11.74)	(-11.82)	(-11.76)	(-11.63)
SD	-11.657***	-3.956***	-3.842***	-3.852***
	(-3.15)	(-3.13)	(-3.17)	(-3.15)
PAY	40.572***	13.899***	13.439***	13.234***
	(13.36)	(13.42)	(13.50)	(13.14)
INS	8.043***	2.733***	2.643***	2.666***
	(6.73)	(6.69)	(6.75)	(6.75)
CL	20.547***	7.242***	6.629***	6.672***
	(3.83)	(3.94)	(3.76)	(3.77)
_cons	31.748***	9.969***	10.402***	11.372***
	(3.30)	(3.02)	(3.29)	(3.59)
N	310	310	310	310
R^2	0.593	0.588	0.599	0.593
adj. R^2	0.536	0.530	0.542	0.536

Note: (1) Dependent variable Total is defined as total financial risk ripple effect, while the DDF, DIF, FF are domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, foreign financing risk ripple effects, respectively. The independent variable PDEP is Digital economy platform index. (2) The data set covers from 2011 to 2020. (3) t statistics are in parentheses. (4) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. (5) All variables are defined in Table 2.

Table 5 presents the results of the impact of the digital economy platform index on financial risk ripple effect. Columns (1) in Table 5 show the impact of digital economy platform index on total financial risk ripple effect. Columns (2) to (4) present the impact of digital economy platform index on domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects, respectively.

The digital economy platform index had an insignificant impact on financial risk ripple effect. From Column (1) of Table 5, we can know that the coefficient of PDEP is -6.040, but it is insignificant at the 10% statistical level. This suggests that digital economy platform index exerts insignificant impact on total financial risk ripple effect. Then, we divide the total financial risk ripple effect into domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects. In Columns (2) to (4), the coefficients of PDEP are -1.980, 2.037, and -2.026, which are insignificant at the 10% level. This suggests that the digital economy platform index has no significant influence on the domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects, respectively. From what has been discussed above, the digital economy platform index has an insignificant impact on the financial risk ripple effect, whether total financial risk ripple effect or domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects.

Table 6 presents the results of impact of the digital economy user index on financial risk ripple effect. Column (1) in Table 6 shows the impact of digital economy user index on total financial risk ripple effect. Columns (2) to (4) present the impact of the digital economy user index on domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects and foreign financing risk ripple effects, respectively.

Table 6. The impact of PDEU on Financial risk ripple effect.

	(1) Total	(2) DDF	(3) DIF	(4) FF
PDEU	-30.183**	-10.409**	-9.956**	-9.814**
	(-2.19)	(-2.19)	(-2.20)	(-2.18)
EDU	10.505***	3.729***	3.326***	3.452***
	(3.02)	(3.11)	(2.91)	(3.02)
PCC	-2.343***	-0.793***	-0.781***	-0.769***
	(-4.65)	(-4.54)	(-4.73)	(-4.67)
CS	-42.570***	-14.673***	-13.926***	-13.974***
	(-11.04)	(-11.14)	(-11.04)	(-10.93)
SD	-9.008**	-3.048**	-2.966**	-2.987**
	(-2.55)	(-2.53)	(-2.56)	(-2.56)
PAY	38.438***	13.177***	12.729***	12.532***
	(12.80)	(12.85)	(12.95)	(12.59)
INS	7.250***	2.462***	2.381***	2.408***
	(6.39)	(6.35)	(6.40)	(6.41)
CL	18.061***	6.389***	5.806***	5.860***
	(3.54)	(3.65)	(3.47)	(3.48)
_cons	51.146***	16.768***	16.753***	17.614***
	(3.87)	(3.69)	(3.86)	(4.07)
N	310	310	310	310
R^2	0.622	0.617	0.627	0.621
adj. R^2	0.568	0.563	0.575	0.567

Note: (1) Dependent variable Total is defined as total financial risk ripple effect, while the DDF, DIF, FF are domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, foreign financing risk ripple effects, respectively. The independent variable PDEU is digital economy user index. (2) The data set covers from 2011 to 2020. (3) t statistics are in parentheses. (4) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. (5) All variables are defined in Table 2.

The digital economy user index has a significantly negative impact on financial risk ripple effect. From Column (1) of Table 6, we can know that the coefficient of PDEU is -30.183, which is significantly negative at the 5% statistical level. This suggests that when digital economy user index is higher, total financial risk ripple effect will be reduced. It can be seen that both statistically and economically, the digital economy user index has a significant negative relationship with total financial risk ripple effect. Then, we divide the total financial risk ripple effect into domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects. In Columns (2) to (4), the coefficients of PDEU are -10.409, -9.956, and -9.814, which are statistically significant at the 5% level. This suggests that when the digital economy user index is higher, the domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects will be reduced. From what has been discussed above, the financial risk ripple effect, whether total financial risk ripple effect or domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects and foreign financing risk ripple effects, can reduce when digital economy user index improved.

Table 7 presents the results of the impact of the digital economy innovation index on the financial risk ripple effect. Column (1) in Table 7 shows the impact of the digital economy innovation index on the total financial risk ripple effect. Columns (2) to (4) present the impacts of the digital economy innovation index on domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects, respectively.

Table 7. The impact of PDEIN on Financial risk ripple effect.

	(1) Total	(2) DDF	(3) DIF	(4) FF
PDEIN	-19.455***	-6.747***	-6.318***	-6.393***
	(-3.91)	(-3.91)	(-3.89)	(-3.91)
EDU	8.760***	3.130***	2.742***	2.890***
	(2.98)	(3.10)	(2.85)	(2.99)
PCC	-1.883***	-0.633***	-0.634***	-0.616***
	(-4.24)	(-4.09)	(-4.39)	(-4.24)
CS	-48.902***	-16.862***	-15.999***	-16.044***
	(-12.71)	(-12.82)	(-12.71)	(-12.58)
SD	-10.323***	-3.500***	-3.405***	-3.411***
	(-2.90)	(-2.87)	(-2.91)	(-2.90)
PAY	42.141***	14.458***	13.938***	13.744***
	(14.76)	(14.90)	(14.88)	(14.47)
INS	8.011***	2.724***	2.631***	2.655***
	(6.91)	(6.87)	(6.92)	(6.93)
CL	18.307***	6.470***	5.898***	5.934***
	(3.56)	(3.68)	(3.49)	(3.50)
_cons	35.971***	11.555***	11.694***	12.716***
	(4.37)	(4.09)	(4.33)	(4.71)
N	310	310	310	310
R^2	0.620	0.615	0.624	0.619
adj. R^2	0.566	0.561	0.571	0.566

Note: (1) Dependent variable Total is defined as total financial risk ripple effect, while the DDF, DIF, FF are domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, foreign financing risk ripple effects, respectively. The independent variable PDEIN is digital economy innovation index. (2) The data set covers from 2011 to 2020. (3) t statistics are in parentheses. (4) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. (5) All variables are defined in Table 2.

The digital economy innovation index has a significantly negative impact on the financial risk ripple effect. From Column (1) of Table 7, we can know that the coefficient of PDEIN is -19.455, which is significantly negative at the 1% statistical significance level. This suggests that when the digital economy innovation index is higher, total financial risk ripple effect will be reduced. From the economic point of view, on average, an increase of one standard deviation (0.353) in digital economy innovation index leads to a decrease of total financial risk ripple effect equivalent to 61.83% (= -19.455*0.353/11.107) of the sample standard deviation. It can be seen that both statistically and economically, the digital economy innovation index has a significant negative relationship with total financial risk ripple effect. Then, we divide the total financial risk ripple effect into domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects. In Columns (2) to (4), the coefficients of PDEIN are -6.747, -6.318, and -6.393, which are statistically significant at the 1% level. This suggests that when the digital economy innovation index is higher, the domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects will be reduced. From what has been discussed above, the financial risk ripple effect, whether total financial risk ripple effect or domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects, can reduce when digital economy innovation index improved.

Table 8 presents the results of impact of digital economy industry index on financial risk ripple effect. Column (1) in Table 8 shows the impact of digital economy industry index on total financial risk ripple effect. Columns (2) to (4) present the impacts of digital economy industry index on domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects and foreign financing risk ripple effects, respectively.

Table 8. The impact of PDEI on Financial risk ripple effect.

	(1) Total	(2) DDF	(3) DIF	(4) FF
PDEI	-3.408	-1.079	-1.141	-1.204
	(-0.49)	(-0.45)	(-0.50)	(-0.53)
EDU	7.438**	2.663**	2.316**	2.463**
	(2.41)	(2.51)	(2.29)	(2.42)
PCC	-2.660***	-0.905***	-0.885***	-0.869***
	(-5.90)	(-5.81)	(-6.00)	(-5.87)
CS	-46.219***	-15.920***	-15.132***	-15.172***
	(-11.29)	(-11.38)	(-11.30)	(-11.17)
SD	-11.182***	-3.802***	-3.682***	-3.690***
	(-3.01)	(-2.99)	(-3.01)	(-3.00)
PAY	40.010***	13.712***	13.249***	13.050***
	(13.19)	(13.26)	(13.34)	(12.96)
INS	7.974***	2.710***	2.620***	2.644***
	(6.61)	(6.57)	(6.62)	(6.62)
CL	19.953***	7.051***	6.429***	6.467***
	(3.72)	(3.83)	(3.65)	(3.66)
_cons	28.553***	8.886**	9.317***	10.358***
	(2.77)	(2.50)	(2.75)	(3.06)
N	310	310	310	310
R^2	0.591	0.586	0.597	0.591
adj. R^2	0.534	0.528	0.540	0.534

Note: (1) Dependent variable Total is defined as total financial risk ripple effect, while the DDF, DIF, FF are domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, foreign financing risk ripple effects, respectively. The independent variable PDEI is digital economy industry index. (2) The data set covers from 2011 to 2020. (3) t statistics are in parentheses. (4) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. (5)

All variables are defined in Table 2.

Digital economy industry index has an insignificant impact on financial risk ripple effect. From Column (1) of Table 8, we can know that the coefficient of PDEI is -3.408, but it is insignificant at the10% statistical level. This suggests that the digital economy industry index exerts insignificant impact on total financial risk ripple effect. Then, we divide the total financial risk ripple effect into domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects. In Columns (2) to (4), the coefficients of PDEI are -1.079, -1.141, and -1.204, which are insignificant at the 10% level. This suggests that the digital economy industry index has no significant influence on the domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects, respectively. From what has been discussed above, the digital economy industry index has an insignificant impact on the financial risk ripple effect, whether total financial risk ripple effect or domestic direct financing risk ripple effects, domestic indirect financing risk ripple effects, and foreign financing risk ripple effects.

5. Conclusions

Based on the data of fund flow (financial transaction) from 2011 to 2020, this paper uses the fund flow analysis method and the inverse principle of Leontief to build a ripple effect model for measuring the ripple effect of financial risks. Then, this paper constructs a panel regression model to study the impact of the digital economy on financial risk ripple effect. In addition, this paper explores the heterogeneous effects of different dimensions of digital economy on financial risk ripple effects. This paper draws the following conclusions.

First, the total ripple effect of financial risks during 2011–2020 is constantly changing, and the ripple effects of different types of risks are heterogeneous. Second, the digital economy has a negative impact on the ripple effect of financial risks. Third, different dimensions of the digital economy have a heterogeneous impact on the ripple effect of financial risks. Specifically, digital economy user index and digital economy innovation index have a negative impact on financial risk ripple effect. Digital economy platform index and digital economy industry index have no significant influence on financial risk ripple effect.

These findings provide several important policy implications. On the one hand, China can strengthen the digital economy to support the real economy, combine the various dimensions of the digital economy, formulate relevant policies, and guide the digital economy to provide strong support for financial risk monitoring, so as to achieve high-quality financial development. On the other hand, China can strengthen the supervision of financial instruments, comprehensively and effectively evaluate the pricing mechanism of financial instruments, establish classified supervision rules and standards, and strengthen and standardize the supervision before, during, and after the event to improve the risk monitoring of financial markets and effectively reduce the risk spread effect of stock default.

Future research could be conducted on at least three fronts. First, future research can further explore the impact of the digital economy on the ripple effect of financial risks from a global perspective. Second, due to data limitations, this paper only studies the impact of the digital economy on the ripple effect of financial risks spanning from 2011–2020. Therefore, future research can expand the data to 2011–2023. Third, further research can expand the data into capital stock data to calculate financial risk ripple effect and expand the data into semi-annual data, which is easier to explore for the impact of the digital economy on financial risk ripple effect.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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