Digital Supply Chain Finance, Financing Constraints and Firm Independent Innovation: Evidence from Emerging Industries

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Keywords: Digital supply chain finance, financing constraints, firm independent innovation

Abstract: Previous studies have explored the impact of supply chain finance on financing constraints, but there is less literature discussing the impact of digital supply chain finance on financing constraints. In this paper, we select the data of 6,295 China's firms in emerging industries from 2011 to 2021 as a sample, and study the impact of digital supply chain finance on firms' independent innovation and the mediating role of financing constraints. The empirical results show that digital finance can empower traditional supply chain finance. Digital supply chain finance has a substitution effect on traditional supply chain.

1. Introduction

Traditional supply chain finance (SCF) refers to the model in which traditional financial institutions provide financial support and financing services to firms in the supply chain through credit and loans. This model usually relies on the credit records and assets of firms as guarantees, and the process is more cumbersome, time-consuming and expensive (Smith and Johnson, 2019). Traditional SCF has problems such as information asymmetry, financing difficulties and high risks, which restrict the development and cooperation of supply chain parties. At present, the mainstream research direction is on digital transformation of firms and traditional SCF, and there is a lack of research related to digital supply chain finance (DSCF). Financing in the traditional SCF model relies on firm credit and bank loans, facing challenges such as long financing cycles, high costs and difficult risk control. DSCF realizes information sharing and capital flow among supply chain parties by establishing a transparent, efficient and safe financial network, which improves financing efficiency, reduces financing costs, shortens the capital turnover cycle and promotes stability and development of the supply chain (Brown and White, 2022). Therefore, this paper hopes to explore whether DSCF can replace traditional SCF and enhance a firm's independent innovation capability by constructing new indicators to measure DSCF[1-3].

This paper adopts quantitative and qualitative analysis methods to study the relationship between DSCF, financing constraints and firms' independent innovation. This paper summarizes the theoretical foundation by reviewing the literature and constructs a theoretical analysis framework. The sample of this paper comes from emerging industries, which refers to those firms that specialize in researching, developing and applying the latest scientific developments and technologies. These firms tend to focus on technological innovation and invest a larger amount in scientific research. Taking such firms as the research object can more intuitively reflect the impact of DSCF on the independent innovation of firms. Therefore, this paper selects and processes the data of emerging firms from 2011 to 2021 according to the needs of the research. Through empirical analysis, this paper demonstrates the substitution effect between digital supply chain finance and traditional SCF in the impact they have on firms' independent innovation. The implementation of DSCF can alleviate a firm's financing constraints, thus enhancing the firm's ability of independent innovation.

The main contributions of this paper are as follows: Firstly, the paper proposes a measure that reveals the impact of DSCF on corporate financing structure, the driving force for corporate innovation and the significant value of digital technology within the SCF system. Secondly, through empirical analysis of emerging industries, the paper provides direct evidence of the impact of DSCF

  DOI: 10.25236/eeim.2024.001

on corporate innovation in the field of emerging industries. The research results have clarified the internal logical relationship between DSCF, corporate financing structure adjustment, and innovation capability enhancement, filling a gap in empirical research in this field. Thirdly, based on the research findings, the paper provides specific recommendations for policymakers on how to strengthen the optimization of corporate financing structure and the improvement of innovation capability by promoting the development of DSCF. These recommendations are of significant importance for guiding policy formulation, promoting the development of emerging industries, and enhancing the national innovation system. Fourthly, this study provides direction and theoretical basis for further exploration of the differences in the use of DSCF among different types and sizes of firms, or the impact mechanism of DSCF on corporate innovation under different economic environments[4-8].

The remainder of the paper is structured as follows. In the next section, we present the main theoretical perspectives used in the research. In Section 3, we present the data that serves as the basis of this research. We formalize our empirical strategy in Section 4 and demonstrate the baseline results. In Section 5, robustness and sensitivity analysis are carried out based on the research results. The Conclusion is presented in Section 6.

2. Theoretical perspectives

2.1 Traditional supply chain finance

SCF originated in the 1980s when global firms sought cost efficiencies through outsourcing. Since then, it has been adopted by a wide range of industries to provide financing and services that support the entire supply chain. It improves supply chain efficiency and sustainability (Hofmann, 2005). On the one hand, SCF reduces financial risks by assessing and controlling risks. On the other hand, SCF facilitates accurate risk assessment by financial institutions by ensuring that the participants' interests are safeguarded through information sharing among supply chain members (Pfohl and Gomm, 2009). Over the past decades, scholars have continued to explore ways to optimize SCF in order to safeguard the interests of financial institutions and participants (Lambert and Cooper, 2000).

However, the problems of traditional SCF have become more and more significant as firms grow larger. In traditional SCF, financial institutions often require core firms to confirm the firms' rights, thereby increasing their financial and administrative costs (Gelsomino, 2016). Complex management systems amplify risk from one-to-one to one-to-many, influencing banks to favor less risky and less complex business models and limiting support for corporate financing needs (Lekkakos and Serrano, 2016)[9-11].

2.2 DSCF

Driven by the development of digital technologies, SCF has stepped into the era of innovation, transformation and upgrading. Thanks to the application of technologies such as big data, cloud computing and blockchain, DSCF is able to present a complex network structure. The participating subjects in the SCF platform are infinitely expanded, and the operational structure of upstream and downstream node firms in the supply chain is no longer limited to the traditional chain organization, which formed an energy-coupled cluster network organization.

Compared with traditional SCF, and with the integration of digital technologies, DSCF displays the characteristics of precision management services and intelligent risk control, which can break through the bottlenecks that hinder the high-quality development of firms in traditional supply chain financial services in many ways, and provide diversified financial services for more and more firms in the supply chain financial ecology. For example, big data technology promotes information sharing and collaboration among supply chain links, enhancing the overall stability and risk resistance of the supply chain. By sharing information and resources, firms in the supply chain can work together to improve credit ratings and reduce the financing costs of the entire supply chain (Choi et al., 2018). In addition, blockchain technology can ensure transparency of information in the supply chain. This transparency of information reduces the information asymmetry problem of financial institutions in the financing process, enabling them to more accurately assess the credit risk and business performance of firms (Wang et al., 2018).

Therefore, it is necessary to improve the efficiency and reduce the cost of SCF through information sharing and technological innovation (Wang et al., 2016). DSCF is of great practical significance to alleviate financing constraints. Information sharing between upstream and downstream firms in the chain can be helpful for supervising the debtor's decision-making, thus effectively alleviating the information asymmetry problem, and at the same time, it can also reduce supervisory cost, improve supervisory efficiency, and reduce the agency cost. Therefore, we propose the original hypothesis:

Hypothesis 1: The implementation of DSCF by firms can significantly promote their innovation.

2.3 The mediating effect of financing constraints

Emerging firms are faced with long investment cycles and high costs, thus requiring substantial financial support. However, the vast majority of emerging firms do not have high credit ratings for debt servicing and have low access to financial support. In addition, investors often assess investments based on return ratios, investing only when returns significantly exceed costs. The return on investment in R&D tends to have a high degree of uncertainty. David (2018) also notes that financing constraints negatively impact innovation performance. Through the implementation of DSCF, firms use liquid assets for collateralized loans from financial institutions. Guarantees form core firms enable financial institutions to mitigate information asymmetry concerns, thus improving lending willingness and enabling effective external financing. Therefore, DSCF can alleviate financing constraints, broadening financing channels and enhancing innovation performance. Therefore, we put forward the following hypotheses:

Hypothesis 2: The implementation of digital finance and supply chain finance by firms can help alleviate the degree of corporate financing constraints.

Hypothesis 3: Financing constraints have a mediating role in the relationship between supply chain finance and innovation performance[12-15].

3. Data

3.1 DSCF

Data studied in this paper on DSCF are extracted from the Wind database. Since SCF includes accounts receivable as collateral and bill discount financing, which is represented as short-term loans and notes payable in financial statements, this paper draws on the SCF measurement methods adopted by Wang Liqing (2018). That is, SCF = (short-term loans + notes payable) / total assets is used to measure the level of firm SCF. Meanwhile, in order to measure the digitalization level of SCF, the Peking University digital financial inclusion index of China (DFIIC) compiled by Guo Feng et al. (2020) is used as the reference variable for the development level of DSCF. In order to study quantitative DSCF, we set an interaction term: DSCF = SCF*DFIIC, which is used to measure the development level of DSCF.

3.2 Financing constraints

Data on Financing constraints are also drawn from the Wind database. Since Fazzari (1988) introduced the concept of financing constraints in 1988, scholars have investigated whether firms experience these constraints by examining various firm attributes. Building on this, they have introduced a range of attribute combinations to establish classification standards for measuring the degree of firms' exposure to financing constraints. These attributes typically include firm size, bond credit ratings, and relationships with conglomerates. However, these attribute combinations often focus on specific factors and may be incomplete, thus failing to provide a comprehensive reflection of firms' overall financing constraints.

Kaplan and Zingales (1997) developed an index called the KZ index to gauge financing constraints. This index, a scoring system, utilizes various financial data to generate a composite score measuring a firm's level of financing constraints. Subsequently, other scholars have made enhancements and innovations to this index. Whited and Wu (2006) delved deeper into this index and created a new one, known as the WW index, which incorporates quarterly financial statement data. However, financial indicators often suffer from endogeneity issues, which can impact the accuracy of the indicators and lead to errors in empirical findings. To address these concerns, Hadlock and Pierce (2010) further refined the KZ index. Their research integrated fundamental financial characteristics to classify firms into different categories, aiming to overcome the shortcomings of other indicators. They utilized the Probit model to construct the financing constraints index calculation formula and classify firms into five categories, each representing varying degrees of financing constraints. The resulting index was termed the SA index. Compared to other indicators, the SA index can mitigate endogeneity problems associated with variables, making it a preferred choice for many scholars in measuring the degree of financing constraints.

This paper adopts this formula directly to calculate the SA index, providing a direct measure of the degree of firms' financing constraints. Size represents the natural logarithm of total assets in millions, and Age denotes the number of years the firm has been listed. The SA index calculated using this formula is always negative, with higher values indicating greater financing constraints faced by the firm. According to the formula of SA index of Hadlock and Pierce, this paper calculates the SA index of each firm's observation year. The more negative and absolute value of SA index, the more serious the degree of financing constraints of the firm (Ju et al., 2013)[16-19].

3.3 Independent innovation of firms

Data on independent innovation of firms are extracted from the Wind database. In this paper, whether or not a firm owns a patent (Innovation1) is taken as the first criterion to measure the independent innovation ability of firms. In this way, firms with independent innovation ability are separated out, and the direct relationship between the innovation ability of firms and the DSCF and financing constraints is briefly analyzed. In most of the existing literature, researchers prefer to use the number of patent applications to measure innovation ability. However, the innovation ability of firms is not only reflected in quantity, but also in quality. Therefore, the number of patent applications (Innovation2) and the success rate of patent applications (Innovation3) are taken as the other two measures in this paper.

3.4 Control variables

Table 1 Summary statistics

VARIABLES	Obs.	Mean	S.D.	Min	Max
Explained variables					
Innovation1	6295	0.588	0.492	0.000	1.000
Innovation2	6295	0.833	1.745	0.000	9.737
Innovation3	6295	0.184	0.059	0.000	1.000
Key explanatory variables					
DSCF	6295	73.033	60.682	0.000	748.699
SCF	6295	0.336	0.244	0.000	2.441
Index aggregate	6295	214.580	74.767	30.910	359.683
Control variables					
ROA	6295	0.049	0.041	-0.014	0.482
MBRG	6295	0.340	1.378	-1.715	72.067
FL	6295	1.511	2.722	-13.953	86.692
TA(10^8 yuan)	6295	148	421	0.818	6160
DTAR	6295	0.413	0.194	0.011	0.975
NOE	6295	7.851	1.221	3.332	12.571
Mediators					
SA	6295	-3.783	0.250	-4.522	-3.020
KZ	6295	0.940	2.220	-6.439	8.134
FC	6295	0.464	0.274	0.002	0.962

In order to reduce the impact of missing variables, the control variables selected in this paper are: rate of return on total assets (ROA); Revenue growth rate(MBRG), which is the difference between the current year's operating revenue and the previous year's operating revenue divided by the previous year's operating revenue; Financial leverage(FL), where the financial leverage factor is equal to the percentage change in earnings per share divided by the percentage change in EBIT; Number of employees(NOE); Total assets(TA); Debit to asset ratio(DTAR).

Table 1 summarizes the statistics of the variables used in this paper. A total of 6,295 firms were studied, of which 58.8% had independent innovation behaviors. The average patent application success rate was 18.94%.

4. Empirical strategy and results

4.1 Empirical strategy

Based on the three hypotheses presented in section 2.2 and section 2.3, we set up equations (1) to (3), respectively. The model specification takes the following forms:

$$Innovation_{i,c,t} = \beta_0 + \beta_1 SCF_{i,t} * DFIIC_{c,t} + \beta_2 X_{i,c,t} + \theta_i + \sigma_t + \varepsilon_{i,c,t} \quad (1)$$

$$Financing\ Constraints_{i,c,t} = \beta_0 + \beta_1 SCF_{i,t} * DFIIC_{c,t} + \beta_2 X_{i,c,t} + \theta_i + \sigma_t + \varepsilon_{i,c,t} \quad (2)$$

$$Innovation_{i,c,t} = \beta_0 + \beta_1 SCF_{i,t} * DFIIC_{c,t} + \beta_2 Financing\ Constraints_{i,c,t} + \beta_3 X_{i,c,t} + \theta_i + \sigma_t + \varepsilon_{i,c,t} \quad (3)$$

Where *i* indexes firms, *c* indexes cities and *t* indexes years; The explained variable is $Innovation_{i.c,t}$, which represents the independent innovation capacity of firms; $SCF_{i,t}$ indicates SCF; $DFIIC_{c,t}$ indicates digital finance; In this paper, we use the interaction term of these two as a measure of DSCF; $X_{i,c,t}$ contains all controls in the equation, which includes total assets, revenue growth rate, financial leverage, number of employees, total assets and debit to asset ratio. $Financing\ Constraints_{i,c,t}$ is represented by SA index and KZ index. As for equation (1), the coefficient of DSCF is β_1. We expect β_1 to be positive. In equation(2), we expect that DSCF can reduce the financing constraints. Therefore, β_1 should be negative. Equation (3) is used to verify the existence of the mediating effect of financing constraints. The coefficient of DSCF is β_1 and the coefficient of financing constraints is β_2. We expect β_1 to be positive and β_2 to be negative.

4.2 Baseline Results

Baseline regression examines the impact of DSCF on firms' autonomous innovation. The results are shown in Table 2. We examined the results from both quantitative and qualitative perspectives. The results show that both digital finance and traditional SCF can promote independent innovation of firms. Meanwhile, digital finance plays a substitute role for traditional SCF. In addition, both digital finance and traditional SCF have no effect on the success rate of patent applications. Therefore, hypothesis 1 does not hold.

The explanatory variable for the results in column 1 and column 2 is whether the firm has patent applications. From the results in column 1, it can be seen that for every unit of SCF, the independent innovation capacity of the firm increases by 23.8 percentage points. For every unit of digital finance, the independent innovation capacity of the firm increases by 0.2 percentage points. However, when both of them work together to have an impact on the independent innovation capacity of a firm, they cause the independent innovation capacity of the firm to decrease by 0.1 percentage points. The results show that there is a substitution effect between digital finance and SCF. In column 2, we add control variables, but the results remain robust. The explanatory variable for the results in column 3 and column 4 is the number of patent applications filed by firms. The column 3 interaction term results are similar to the results of column 1. In column 4, we similarly include control variables, but the results remain robust. The explanatory variables for the results in column 5 and column 6 are firms' patent application success rates. By choosing patent application success rate as the explanatory variable, we hope to analyze qualitatively the impact of the three independent variables on firms' capacity to innovate. The results show that digital finance, traditional SCF and DSCF do not have any effect on firms' capacity for independent innovation[20-21].

Table 2 Effects of digital supply chain on innovation: Baseline Estimates

	Innovation1		Innovation2		Innovation3	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
DSCF	-0.001***	-0.001**	-0.001*	-0.002*	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
SCF	0.238***	0.255**	0.293	0.543*	-0.060	-0.011
	(0.088)	(0.096)	(0.216)	(0.276)	(0.118)	(0.153)
DFIIC	0.002***	0.002***	0.002	0.003	0.000	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
ROA		-0.278		-0.480		0.190
		(0.184)		(0.587)		(0.523)
MBRG		-0.002		-0.001		-0.005
		(0.005)		(0.014)		(0.018)
FL		-0.003		0.003		-0.007**
		(0.003)		(0.007)		(0.003)
TA		-0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)
DTAR		-0.172***		0.033		0.051
		(0.044)		(0.202)		(0.244)
NOE		-0.011		0.201***		-0.051***
		(0.011)		(0.048)		(0.012)
Constant	0.121	0.346*	0.342	-1.363**	0.132	0.316
	(0.110)	(0.176)	(0.489)	(0.568)	(0.312)	(0.282)
Observations	8,752	7,645	8,752	7,645	1,716	1,548
R-squared	0.128	0.140	0.064	0.086	0.092	0.120
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Standard errors in parentheses are clustered in the industry level.

4.3 Robustness checks

In order to minimize the potential correlation between the explanatory variables and the model's error terms and to improve the accuracy of the estimation, this paper selects the lagging one-stage test, which is widely used in finance. This method was proposed by Arellano and Bond (1991). In addition, this paper excludes and re-examines data from the 2015 Chinese stock market crash and the COVID-19 outbreak that began in 2019, respectively, in order to exclude the impact of special events on the economic environment in individual years.

4.3.1 Lagging one-stage test

It may take some time for the effects of SCF in easing corporate financing constraints to be realized. Therefore, this constraint effect has a certain lag. The SCF lagging one period is adopted as the new explanatory variable for the robustness test. From the regression results in Table 3, the coefficient of the interaction term is -0.0009 and significant at the level of 5%, and the conclusion is robust. The rest of the results are basically similar to Table 2.

Table 3 Lagging one-stage test

	Innovation1	
VARIABLES	(1)	(2)
DSCF*lag	-0.0009**	-0.0006*
	(0.0003)	(0.0003)
SCF*lag	0.2462**	0.2252**
	(0.0926)	(0.1057)
DFIIC*lag	0.0020***	0.0019***
	(0.0006)	(0.0006)
ROA		-0.2619
		(0.1904)

MBRG		-0.0053
		(0.0036)
FL		-0.0010
		(0.0026)
TA		-0.0000
		(0.0000)
DTAR		-0.1607**
		(0.0630)
NOE		-0.0034
		(0.0124)
Constant	0.1498	0.3016
	(0.1101)	(0.1834)
Observations	7,061	6,095
R-squared	0.1344	0.1438
Firm FE	YES	YES
Year FE	YES	YES

Notes: *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Standard errors in parentheses are clustered in the industry level.

4.3.2 Rule out the competitive hypothesis of natural disaster risk

In order to exclude the particular impact of natural disasters on the economic environment, we specifically exclude data from the period of the Coronavirus Disease, which began in 2019, and rerun the study. The results in Table 4 show that natural disasters do not have an impact, and the baseline results remain robust.

Table 4 Rule out the competitive hypothesis of natural disaster risk

	Innovation1	
VARIABLES	(1)	(2)
DSCF*natural disaster risk	-0.0001**	-0.0002***
	(0.0008)	(0.0002)
SCF	0.2389**	0.0829***
	(0.0865)	(0.0635)
DFIIC	0.0020***	0.0016***
	(0.0005)	(0.0005)
ROA		-0.2987
		(0.1913)
MBRG		-0.0022
		(0.0050)
FL		-0.0028
		(0.0027)
TA		0.0000
		(0.0000)
DtAR		-0.1900***
		(0.0525)
NOE		-0.0000**
		(0.0000)
DSCF	-0.0008***	
	(0.0003)	
Constant	0.1208	0.3284**
	(0.1121)	(0.1269)
Observations	8,752	7,645
R-squared	0.1282	0.1406
Firm FE	YES	YES
Year FE	YES	YES

Notes: *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Standard errors in parentheses are clustered in the industry level.

4.3.3 Rule out the competitive hypothesis of financial risk

In order to exclude the special impact caused by financial risk, we specifically exclude the data from the Chinese stock market crash in 2015. Based on the results of Table 5, it can be seen that financial risks have no impact, and the baseline results remain robust.

Table 5 Rule out the competitive hypothesis of financial risk

	Innovation1	
VARIABLES	(1)	(2)
DSCF*financial risk	-0.0005**	-0.0004***
	(0.0003)	(0.0003)
SCF	0.1212**	0.0632**
	(0.0833)	(0.0547)
DFIIC	0.0018***	0.0015**
	(0.0006)	(0.0006)
ROA		-0.2774
		(0.1820)
MBRG		-0.0026
		(0.0048)
FL		-0.0030
		(0.0026)
TA		-0.0000
		(0.0000)
DTAR		-0.1739***
		(0.0442)
NOE		-0.0106
		(0.0108)
DSCF	-0.0004	
	(0.0003)	
Constant	0.1647	0.4112**
	(0.1302)	(0.1746)
Observations	8,752	7,645
R-squared	0.1286	0.1401
Firm FE	YES	YES
Year FE	YES	YES

Notes: *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Standard errors in parentheses are clustered in the industry level.

4.4 Heterogeneity of firm property

The regression results are shown in Table 6. In column 1, the coefficient of DSCF for state-owned firms is negative. In contrast, in column 2, the coefficient of DSCF for private firms is positive and significant at the level of 1%. Therefore, DSCF promotes the independent innovation capability of private firms. The main reason for the negative coefficient of DSCF may be that state-owned firms have institutional and resource advantages and do not necessarily need to obtain financial support for innovation through SCF, but private firms are more likely to need to obtain more funds for innovation through the implementation of DSCF.

Table 6 Heterogeneity of firm property

	Innovation1	
VARIABLES	State-owned	Private
DSCF*state-owned	-0.0002*	
	(0.0001)	
DSCF*private		0.0002***
		(0.0001)
SCF	0.2568***	0.2669***
	(0.0868)	(0.0876)
DFIIC	0.0019***	0.0019***

	(0.0005)	(0.0005)
Constant	0.1331	0.1299
	(0.1135)	(0.1133)
Observations	8,752	8,752
R-squared	0.1287	0.1292
Firm FE	YES	YES
Year FE	YES	YES

Notes: *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Standard errors in parentheses are clustered in the industry level.

5. Mechanisms

5.1 The relationship between digital supply chain finance and financing constraints

Table 7 reports the relationship between firms' implementation of SCF and financing constraints. The test results show that the regression coefficient of DSCF is -0.0008 and significant at the level of 1%. The results indicate that the implementation of DSCF by firms can help to alleviate the degree of corporate financing constraints. The empirical results give support to the hypothesis 2.

Table 7 The relationship between digital supply chain finance and financing constraints

	SA	
VARIABLES	(1)	(2)
DSCF	-0.0008***	-0.0004***
	(0.0001)	(0.0001)
SCF	0.2215***	0.1742***
	(0.0439)	(0.0373)
DFIIC	0.0015***	0.0009***
	(0.0004)	(0.0003)
ROA		-0.0208
		(0.1431)
MBRG		0.0005
		(0.0014)
FL		0.0009
		(0.0009)
TA		0.0000***
		(0.0000)
DTAR		-0.2234***
		(0.0277)
NOE		-0.0000
		(0.0000)
Constant	-4.1285***	-3.9448***
	(0.0830)	(0.0596)
Observations	8,511	7,534
R-squared	0.3089	0.4083
Firm FE	YES	YES
Year FE	YES	YES

Notes: *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Standard errors in parentheses are clustered in the industry level.

5.2 The mediating effect of financing constraints

Since in the baseline regression, we do not find that digital finance and SCF have an effect on firms' quality of innovation, we only use Innovation1 as the dependent variable in this test. We use SA index and KZ index to represent the level of financing constraints, respectively. The results are shown in Table 8. The results of both indices indicate that financing constraints have a mediating effect in the relationship between DSCF and innovation performance. Digital finance and SCF improve the independent innovation capability of firms by reducing their financing constraints level.

The empirical results also give support to hypothesis 3.

Our regression using the SA index as a measure of the financing constraints level yields the results in column 1 and column 2. According to the results in column 1, each unit increase in the SA index decreases the firm's ability to innovate by 0.9 percentage points. Column 2 shows the results including control variables, which remain robust.

In the results shown in column 3, we have chosen the KZ index as the measure. The results are broadly consistent with the results in the first and second columns. In column 4, we similarly include control variables, but the results remain robust.

Table 8 The mediating effect of financing constraints

	Innovation1			
VARIABLES	(1)	(2)	(3)	(4)
SA	-0.1372**	-0.1436**		
	(0.0589)	(0.0574)		
KZ			-0.0155***	-0.015***
			(0.0037)	(0.0052)
DSCF	-0.0007**	-0.0002	-0.0008***	-0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
SCF	0.2294**	0.1839*	0.2927***	0.2275**
	(0.1028)	(0.1034)	(0.0908)	(0.1039)
DFIIC	0.0017***	0.0015**	0.0017***	0.0015***
	(0.0005)	(0.0005)	(0.0004)	(0.0005)
ROA		-0.1712		-0.5097*
		(0.2879)		(0.2605)
MBRG		-0.0018		-0.0022
		(0.0048)		(0.0050)
FL		-0.0033		-0.0031
		(0.0025)		(0.0024)
TA		-0.0000		0.0000
		(0.0000)		(0.0000)
DTAR		-0.1444*		-0.0789
		(0.0771)		(0.1099)
NOE		-0.0000**		-0.0000**
		(0.0000)		(0.0000)
Constant	0.7024**	0.8539***	0.1898**	0.2868**
	(0.2923)	(0.3076)	(0.0903)	(0.1412)
Observations	8,511	7,534	8,004	7,089
R-squared	0.1354	0.1472	0.1366	0.1465
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Standard errors in parentheses are clustered in the industry level.

6. Conclusion

This paper studies the impact of DSCF on firm innovation. The experimental results show that both digital finance and SCF promote innovation and substitutability exists between digital finance and SCF. Therefore, we can infer that DSCF can replace traditional SCF. The conclusion provides corroborating evidence that the digital development of SCF is beneficial. The vast array of technologies in digital finance can empower SCF business. Therefore, DSCF can change the lack of coordination among the parties under the traditional SCF model. In addition, this paper finds that DSCF can increase the R&D spending of firms by alleviating the degree of their financing constraints, thus enhancing their innovation performance. In the heterogeneity test, we find that the impact of DSCF on private firms is significantly greater than on state-owned firms.

The findings imply that government agencies and financial institutions should actively promote open sharing of electronic service information, promote the full application of various types of data in the digital production system, and jointly empower the innovative development of DSCF to create a better financing environment for science and technology-based firms.

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