Current Science
CS 5 (3), 2573-2592 (2025)
Received 21 Feb 2025 | **Revised** 10 March 2025 | **Accepted** 24 April. 2025 | **Online Available** 23 May 2025
https://doi.org/ 10.52845/CS/2025-5-3-41

Current Science
Current Science

OPEN ACCESS
ISSN (O) 2795-8639

Original Article

Does Red Culture Benefit Big Data Technology Innovation? Evidence from Chinese Cities

Xiang Cheng, Yuqing Cui

[1]School of International Studies, Sichuan University, Chengdu, China

[2]School of Economics and Management, Aba Teachers College, Aba prefecture, Sichuan Province, China

[*]Corresponding Author: Yuqing Cui

Abstract:
How does red culture affect city big data technological innovation? Based on theoretical analysis, this paper conducts an empirical test based on data from Chinese cities from 2011-2019 to investigate the aforementioned questions. The results show that the continuation of red culture can enhance the positive psychological capital of employees and the psychological ownership of enterprises, both of which are conducive to enterprise innovation and thus can promote big data technology innovation; the stronger the continuation of red culture in a region, the higher its level of big data technology innovation. Based on the promotion effect on enterprise innovation, the continuation of red culture can promote the development of regional financial technology in the financial sector and improve the level of regional technological innovation in the real sector. Based on demand pull, information symmetry, and risk-taking, fintech development can enhance regional big data technology innovation; based on the synergy effect and knowledge dissemination effect, regional technology innovation can also improve regional big data technology innovation. This study attempts to construct a socialist political economy with Chinese characteristics by adopting the econometric research method of Western economics.

Keywords: Red culture; Financial technology; Technological innovation; Big data technology innovation

Introduction

Data is a novel production factor, and its full potential must be realized to strengthen and expand China's digital economy continuously. The key to unlocking data's role as a factor is big data technology innovation, the underlying technology that empowers the digital economy to be stronger, better, and more extensive. The continuation of red culture is vital to everyone in the Chinese government, irrespective of age and population (Chen and Huang 2021), including employees dedicated to big data technology innovation. Therefore, understanding how the continuation of red culture will impact big data technology innovation is crucial to practically promote the development of China's digital economy, enhance cultural self-confidence, and raise consciousness on continuing red culture theoretically.

The red spirit is the core element of red culture, and it is interchangeable with the red gene. This study examines three aspects of the red gene and red spirit. Firstly, the connotation of the red gene encompasses spiritual qualities such as ideals, beliefs, purpose, party spirit, and work style formed by the Communist Party of China during the revolutionary war years (Chen and Huang 2021). The red spirit, on the other hand, is a spirit of struggle that encompasses qualities such as faith and innovation, self-reliance, hard work, loyalty to ideals, honesty, selfless dedication, and courageous sacrifice (Zhang 2011). Secondly, the characteristics of the red spirit can be attributed to the informal system of the North (Chen and Huang 2021). In the new era, the red spirit remains a valuable spiritual wealth of the Chinese nation and the Communist Party of China (Peng and Jiang 2021). Thirdly, the role of the red gene and red spirit in the new era of socialism with Chinese characteristics. The red gene serves as an ideological beacon guiding the Chinese nation's direction (Chen and Huang 2021), while the red spirit is the spiritual force driving the great rejuvenation of the Chinese nation and is integrated deeply into the cultural gene and spiritual bloodline of the Chinese nation. It is a powerful internal energy for the Party to lead the people to build a solid socialist modern country and achieve the great rejuvenation of the Chinese nation (Cao 2021; Peng and Jiang 2021).

Big data technology innovation is a science and technology innovation type, and various factors can influence its development. Another type of research closely related to this paper is the literature on the factors influencing science and technology innovation, which mainly focuses on (1) government policies. Government investment in R&D and subsidies, as well as localization rate protection, can promote technology innovation (Doh and Kim 2014; Fu et al. 2015; Guo, Guo, and Jiang 2016). Additionally, establishing high-tech zones drives urban investment clustering and promotes technology innovation (Li and Yang 2019), while urbanization can also boost technological innovation (Lu and Li 2021). (2) Economic factors. The agglomeration of finance, education, and manufacturing can promote science and technology innovation (Zhou and Pang 2019), and social capital, such as social networks and trust levels, is also conducive to technology innovation (Gu, Lyu, and Yang 2019). Moreover, opening high-speed rail can improve regional innovation and promote technology innovation (Bian, Wu, and Bai 2019). (3) Foreign investment. Research on FDI and science and technology innovation has been particularly active, resulting in three theories: the promotion theory, the irrelevance theory, and the harmful theory. The promotion theory argues that FDI has a facilitating effect on technology innovation (Keller 2002), the irrelevance theory argues that FDI does not have a significant impact on technology innovation (Henny and Manuel 2002), and the harmful theory argues that FDI is not conducive to increasing firms' incentives for technology innovation and is instead harmful to technology innovation (Jiang and Xia 2005). Overall, current literature has rarely conducted any special studies on the influencing factors of technological innovation in big data.

Compared with the existing literature, this paper offers potential contributions in several ways. Firstly, it provides empirical evidence for the influencing factors of big data technology innovation. Although many studies have been conducted on the factors affecting science and technology innovation, fewer have addressed the factors affecting big data technology innovation. This paper examines the impact of continuing the red culture on big data technology innovation and its mechanism, providing supporting evidence for the factors influencing it. Secondly, it enriches the literature on the impact of continuing the red culture. While the role of continuing the red culture has been studied extensively in the existing literature, its effect on big data technology innovation has not been explored. This paper investigates the impact of continuing the red culture on big data technology innovation and its mechanism, contributing to the literature on its impact. Thirdly, it aims to improve the initiative of continuing the red culture. Drawing on theoretical analysis and empirical testing, this paper concludes that continuing the red culture promotes technological innovation and financial technology development, which is conducive to big data technology innovation. This research conclusion has important implications for encouraging local governments and enterprise sectors to proactively continue the red culture.

The subsequent sections of this paper are arranged in the following manner: Section 2 furnishes a theoretical analysis and introduces the research hypothesis; Section 3 presents the research design; Section 4 entails an empirical analysis and robustness test, whereas Section 5 comprises a mechanism test. Finally, the paper concludes with an overall summary, providing insights into the research topic.

1. Theoretical Developments and Hypotheses

Big data technology innovation is a form of enterprise innovation, and this paper posits that adhering to a continuing red culture can positively influence the psychological capital of corporate employees. Consequently, they may develop psychological ownership of the company, thereby fostering enterprise innovation and, ultimately, promoting big data innovation. Existing research results inform this argument. The subsequent analysis delves into the specifics.

1.1 Analysis Based on Positive Psychological Capital

In modern economic contexts, it is increasingly important to consider positive psychological capital as an essential component of a productive workforce. Along with tangible assets like human capital, social capital, machinery, and equipment, intangible assets such as positive psychological capital have been identified as crucial factors in business success (Luthans et al. 2004). Positive psychological capital is a psychological state comprising self-confidence, hope, optimism, and resilience (Luthans et al. 2004; Luthans et al. 2008; Sweetman et al. 2011; Xiong et al. 2016). Confidence refers to one's belief in their ability to overcome challenging tasks, hope is a positive motivational state that drives goal achievement through multiple means, optimism denotes positive beliefs about present and future outcomes, and resilience describes one's ability to recover positively from adversity and setbacks (Luthans et al. 2004; Xiong et al. 2016).

Continuing the red culture has been identified as a means of enhancing the positive psychological capital of employees. Red culture represents the political essence of the Communist Party of China and is considered the spiritual source of Chinese Communists in the new era. By promoting the red spirit, enterprises can encourage and support employees' self-confidence, hope, optimism, and resilience, leading to a more productive and engaged workforce. The red spirit is grounded in the self-confidence engendered by Marxism's combination with China's concrete reality, and the spirit of overcoming enemies and difficulties to emerge victorious (Zhang 2011). Enterprises can inspire this spirit of unparalleled self-confidence by promoting the red culture, thus enhancing the self-confidence of enterprise employees. Red culture also promotes hope among employees by creating supportive work environments and linking theory to practice through close contact with the masses (Cao 2021; Zhang 2011). Similarly, enterprises can maintain optimism among employees by demonstrating the revolutionary optimism embodied by the red spirit, which emphasizes a conscious understanding of objective laws in conjunction with robustness, indomitability, endurance of failure, and the revolutionary spirit of pain (Chen 2001). Finally, the red culture enhances resilience by inspiring employees to embody the qualities of steadfastness and courage, unwavering ideal beliefs, and the spirit of struggle to maintain faith (Peng and Jiang 2021; Zhang and Quan 2014). In summary, by continuing the red culture and promoting the red spirit, enterprises can foster a more engaged and productive workforce, characterized by self-confidence, hope, optimism, and resilience. By embodying Marxist principles and Chinese realities, enterprises can encourage the spirit of overcoming enemies and difficulties, thereby enhancing employees' self-confidence. In addition, the red culture can promote a supportive work environment, create a culture of optimism, and strengthen resilience by inspiring the qualities of steadfastness and courage.

Positive psychological capital has been identified as a driver of corporate innovation. In the 21st century, many companies have made innovation a key goal (Mumford et al. 2002), with employees playing a critical role in the innovation process (Scott and Bruce 1994). Positive psychological capital, self-confidence, hope, optimism, and resilience, can facilitate corporate innovation. Firstly, self-confidence is crucial for innovation, as it encourages individuals to engage in risky activities, such as generating viable ideas and implementing them successfully (Gist and Mitchell 1992). Secondly, hopeful individuals can achieve their goals in multiple ways and remain motivated to succeed in their tasks (Avey, Wernsing, and Palanski 2008), making hope a promoter of innovation. Optimism also facilitates innovation by allowing individuals to attribute their failures to specific external factors and maintain their motivation to succeed (Avey, Wernsing, and Palanski 2008). Lastly, resilience helps individuals quickly recover from failures, explore the causes of problems, and seek solutions to overcome difficulties in the innovation process (Luthans et al. 2004). In conclusion, positive psychological capital benefits corporate innovation by enabling individuals to generate and implement innovative ideas while remaining motivated to overcome setbacks and obstacles.

1.2 Analysis Based on Psychological Ownership

Psychological ownership is a psychological state characterized by individuals perceiving a target as "mine" or "ours" (Pierce, Kostova, and Dirks 2001). It is a sense of possession that makes individuals see the target as an extension of themselves (Belk 1988; Pierce, Kostova, and Dirks 2001). This perception affects their attitudes, motivations, and behaviors toward the target (Van Dyne and Pierce 2004; Dai, Su, and Yang 2020). The target can be tangible objects (Van Dyne and Pierce 2004) and intangible objects such as new ideas and strategic plans (Avey, Wernsing, and Palanski 2008). Psychological ownership of the firm by employees occurs when the target object is the firm where they work (Furby 1978; Van Dyne and Pierce 2004).

Continuing the red culture can lead to psychological ownership of the company by employees. Psychological ownership, as defined by Pierce, Kostova, and Dirks (2001), is a state in which individuals perceive an object as "mine" or "ours", resulting in the sense of possession that influences their attitudes, motivations, and behaviors toward the object (Furby 1978; Van Dyne and Pierce 2004). To promote psychological ownership in employees, organizations can appeal to the three main motivations identified by Pierce, Kostova, and Dirks (2001): a sense of home, self-efficacy, and self-identity. The continuation of the red culture and stimulation of the red spirit in China can impact these three motivations, leading to enhanced psychological ownership of the company. The sense of "home" space is critical for developing psychological ownership, and the red culture can contribute to this sense of belonging by evoking positive emotions and enhancing a person's sense of identity (Li et al. 2020). By integrating the red culture into the company culture and fostering a sense of identification with the organization, employees can feel a sense of belonging and a sense of space for "home". To enhance the sense of achievement, the red culture can promote the mass line, which involves respecting employees' initiative and mobilizing their enthusiasm. This can help employees obtain a sense of satisfaction and self-efficacy in their work, leading to psychological ownership of the company. Finally, the red culture can encourage employees to participate in business management, increasing their involvement and promoting self-identity, another motivation for psychological ownership. Overall, continuing the red culture in China is beneficial for promoting psychological ownership of the enterprise by employees.

Psychological ownership can play a crucial role in promoting firm innovation. When people develop a sense of possession towards a particular target, it can have significant behavioral, emotional, and psychological effects (Pierce, Kostova, and Dirks 2001), which in turn can foster innovation. One such effect is the willingness to take risks and assume responsibility. Since corporate innovation is inherently risky, individuals with psychological ownership are likelier to take calculated risks and exhibit greater dedication toward the organization (Pierce, Kostova, and Dirks 2001; Chen and Hui 2012). This sense of ownership also generates a sense of accountability for the target, promoting a greater sense of responsibility toward the firm's innovative pursuits. In addition to promoting risk-taking and responsibility, psychological ownership fosters active input toward innovation. Corporate innovation is a complex project that demands significant employee input, engagement, and dedication (Mumford et al. 2002). When employees develop a strong sense of organizational identity, pride, and ownership, they are more likely to voluntarily invest more energy in the organization (Liu et al. 2019) and contribute beyond their job responsibilities (Dai, Su, and Yang 2020). Consequently, psychological ownership can motivate employees to exhibit more innovative behaviors, enhancing innovation. Furthermore, psychological ownership can also facilitate knowledge sharing among employees, which is essential for corporate innovation. Knowledge sharing often poses challenges due to conflicting interests among employees (Li et al. 2015). However, psychological ownership can help overcome these challenges by promoting a sense of belonging and "home" among employees, which can encourage knowledge sharing and facilitate innovation. Sharing ideas can also lead to additional resources to promote innovation (Scott and Bruce 1994). Therefore, psychological ownership can play a vital role in promoting idea-sharing and knowledge dissemination, thereby fostering innovation. In summary, psychological ownership can significantly facilitate innovation within firms.

1.3 Research Hypothesis

In summary, fostering and reinforcing the red culture can enhance employees' positive psychological capital, including self-confidence, optimism, hope, and resilience, thus promoting their overall well-being. Furthermore, by cultivating a sense of belonging, creating a comfortable and welcoming work environment, providing opportunities for achievement, fostering self-efficacy, encouraging participation, and promoting self-identity, red culture can also promote employees' psychological ownership of their company. Both positive psychological capital and psychological ownership are critical drivers of corporate innovation. As big data technology innovation continues to be a crucial aspect of digital transformation for big data and non-big data enterprises, continuing the red culture can be advantageous for promoting corporate innovation in this area. At the macro level, the more a region fosters its red culture, the more it can stimulate big data technology innovation in enterprises in that region. Therefore, based on these premises, this paper proposes the following research hypothesis.

Hypothesis: *Continuing the red culture can promote big data technology innovation, and the stronger the red culture continues in a region, the higher its level of innovation.*

Based on the role of continuing red culture in promoting enterprise innovation, the mechanism will be studied later from two aspects: financial science development in the financial sector and technological innovation in the real sector.

2. Method and materials

2.1 Data Resources

This paper utilizes the existing literature, such as the work by Qiu, Huang, and Ji (2018), and adopts the Peking University Digital Inclusive Finance Index as a proxy variable to gauge the level of fintech. The index has been available since 2011, and thus, the empirical analysis in this study focuses on Chinese city data spanning from 2011 to 2019. In assessing the strength of red bloodline continuity, there is currently no publicly available data. Therefore, this paper collects information on enterprises that incorporate terms like "red education", "red gene", or "red inheritance" in their names or business scope through an enterprise search. These enterprises are then aggregated by city based on their registered locations, enabling the characterization of the red bloodline's strength using the count of such enterprises in each city.

To measure the level of big data technology innovation, this paper extracts the number of patent applications and licenses related to big data from Wisdom Tooth, using "big data" as the keyword. This serves as an indicator of big data technology innovation across different cities. The data from PatSnap is sourced from the State Intellectual Property Office, which offers a more convenient means of verification. Other data utilized in this study are obtained from reputable sources such as the People's Bank of China, the Ministry of Civil Affairs of China, and the China City Statistical Yearbook.

To mitigate the impact of outliers, this paper employs a technique known as Winsorization to adjust the extreme values of continuous variables. This involves reducing the upper and lower 1% tails of the variables, thus eliminating the influence of outliers on the overall analysis.

2.2 Empirical Model

To test the research hypothesis proposed in the previous section, the following two-way time and individual fixed effects models were designed:

$$DTCH_{it} = \alpha_0 + \beta_1 * RLGD_{it} + \eta * \boldsymbol{X} + \alpha_i + \lambda_t + \varepsilon_{it} \qquad (1)$$

Where, $DTCH_{it}$ denotes the level of big data technology innovation in the t-th year of the i-th city, α_0 is the intercept term, α_i is the individual effect of the i-th city, λ_t is the annual effect of the t-th year, and ε_{it} is the random error term. $RLGD_{it}$ is the key explanatory variable, i.e., the strength of the red culture in the i-th city, and β_1 is its coefficient. If β_1 is significantly positive, then continuing the red culture can promote big data technology innovation. $\boldsymbol{X}$ are the control variables.

2.3 Variables

(1) Dependent variables. The dependent variables utilized in this study revolve around the level of big data technology innovation. Building on previous literature (e.g., Lu, Yang, and Ma 2021), this paper employs two proxy variables to gauge the level of big data technology innovation: the number of big data technology patent applications per capita (*DTCH*) and the number of big data technology patents granted per capita (*rDTCH*). These variables have been identified in the

literature as reliable indicators of the level of big data technology innovation and are therefore employed in this research.

(2) Independent variables. The primary independent variables explored in this research pertain to the strength of red culture continuity. While China possesses abundant regional red education resources, their practical development and utilization remain incomplete (Li 2019). Red spirit, which forms the core of red culture and red genes, are inherited within the same lineage (Chen and Huang 2021). Red resources encapsulate rich red genes and red spirit. Leveraging red education becomes a crucial and practical pathway for transmitting red genes and realizing red inheritance, contributing to the continuity of red culture. Furthermore, red resources thrive within local environments, establishing deep connections with regional cultural characteristics (Li 2019). Consequently, the transmission of red genes and the perpetuation of red culture through red education exhibit local dependencies.

To capture the strength of red culture continuity, this study gathers data on enterprises that incorporate terms such as “red education”, “red gene”, or “red heritage” in their names or business scope through an enterprise search. Subsequently, these enterprises are grouped by their registered locations, enabling the determination of the count of enterprises associated with “red education”, “red gene”, or “red heritage” within each city. The counts of enterprises falling under these three categories are then normalized, resulting in *RLGD*, which serves as a proxy variable representing the strength of red culture continuity.

Additionally, for robustness testing purposes, *rRLGD* is obtained by taking the natural logarithm of the count of the three types of enterprises, with one added to the result. Furthermore, recognizing that general higher education institutions also play a significant role in continuing the red culture, this paper incorporates the sum of the counts of the three types of enterprises and the count of general higher education schools within each city. This combined count is then standardized, yielding *rrRLGD*, which acts as a proxy variable for assessing the strength of red culture continuity. It should be noted that larger values of *RLGD*, *rRLGD*, and *rrRLGD* indicate higher strength in their respective measures.

(3) Control variables. Drawing on the existing literature on technology innovation (e.g., Li and Yang 2019; Lu, Yang, and Ma 2021), this study incorporates several control variables to account for various factors. These control variables include the level of economic development, foreign direct investment, industrial structure, financial development, financial decentralization, investment in research and development (R&D), and government intervention. These variables have been widely recognized in the literature as crucial factors influencing the dynamics of science and technology innovation. By controlling for these variables, this paper aims to isolate the specific impact of the examined factors on the phenomenon under investigation, ensuring a more comprehensive and accurate analysis.

The variables examined in this paper are summarized in Table 1.

Table 1. Definition of main variables.

Type	**Name**	**Symbol**	**Definition**	**References**
Dependent variables	Big data technology innovation	*DTCH*	Number of Big Data technology patent applications/total population	Lu, Yang, and Ma (2021)
		rDTCH	Number of patents granted for big data technologies/total population	
Independent variables	Strength of red culture continuity	*RLGD*	The number of enterprises registered in the city whose name or business scope includes “red education”, “red genes” or “red heritage” (i.e., number of three types of enterprises) and standardized.	
		rrRLGD	The logarithm of the number of three types of enterprises plus one.	
		rrrRLGD	The number of three types of enterprises plus the number of general	

			higher education schools, normalized by (max-x)/(max-min)	
Control variables	Economic Development Level	*PGDP*	The logarithm of the real GDP per capita (with 2011 as the base period)	Chen, Yan, and Chen (2022); Lu, Yang, and Ma (2021); Li and Yang (2019)
	Foreign Direct Investment	*PFDI*	The ratio of foreign direct investment to GDP	
	Industry Structure Level	*INSR*	Measured by 1*proportion of primary industry + 2*proportion of secondary industry + 3*proportion of tertiary industry	
	Financial development Level	*FSIZ*	The ratio of city loan balance to GDP	
	Financial Decentralization	*FIND*	The ratio of city loan balance to national loan balance	
	R&D Investment	*RDEV*	The logarithm of number of city R&D staff	
	Government Intervention	*GOVN*	The ration of urban fiscal expenditure to urban GDP	

3. Empirical Results

3.1 Descriptive Statistics

Table 2 presents the descriptive statistics for the main variables under examination. Analyzing the descriptive statistics reveals several noteworthy observations. Firstly, the mean value of the level of big data technology innovation (*DTCH*), measured by the number of big data technology patent applications, is 0.0752. The minimum value recorded is 0.0000, while the maximum value reaches 4.0150. These findings indicate substantial variations in big data technology innovation across different cities, aligning with the broader national context of uneven development.

Secondly, the mean value of the level of big data technology innovation (*rDTCH*), measured by the number of patents granted, is 0.0141. The minimum value is 0.0000, while the maximum value reaches 0.6391. This observation confirms the considerable disparities in big data technology innovation among cities.

Thirdly, examining the strength of red bloodline continuity, as represented by *RLGD*, the mean value is 0.0688. The minimum value recorded is 0.0000, while the maximum value is 1.0000. The substantial difference between the mean value and the range of minimum and maximum values underscores the uneven development throughout the nation.

Overall, the descriptive statistics provide valuable insights into the distribution and variation of the examined variables, highlighting the heterogeneity in big data technology innovation and the strength of red bloodline continuity across different cities, consistent with the broader national landscape of uneven development.

Table 2. Descriptive statistics of main variables.

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
DTCH	2,298	0.0752	0.2750	0.0000	4.0150
rDTCH	2,298	0.0141	0.0480	0.0000	0.6391
RLGD	2,298	0.0688	0.1608	0.0000	1.0000
FTCH	2,298	1.6320	0.6604	0.2948	2.8197
CTCH	2,298	1.5860	3.0387	0.0090	37.6867
PGDP	2,298	3.7860	0.6937	1.6387	6.1430
FSIZ	2,298	0.2378	0.1140	0.0632	1.2852

FIND	2,298	0.0316	0.0573	0.0013	0.6293
PFDI	2,298	0.0177	0.0178	0.0000	0.1978
INSR	2,298	0.0234	0.0257	0.0183	1.2526
RDEV	2,298	-0.6404	1.1400	-2.9508	2.8885
GOVN	2,298	0.1832	0.1511	0.0116	4.0164

3.2 Baseline Results

The adoption of double clustering (cluster) adjustment in estimating standard errors, both individually and over time, can effectively mitigate issues such as autocorrelation and heteroskedasticity, thereby enhancing the reliability of statistical inference (Chen, Yan, and Chen 2022). Table 3 presents the results from estimating Equation (1), employing individual and temporal double-clustering of robust standard errors. The estimation process includes gradually adding control variables while accounting for individual and annual effects. This approach ensures a comprehensive and robust analysis of the relationships under investigation.

Table 3. Regression results of Equation (1)

	(1)	(2)	(3)	(4)	(5)
Variables	*DTCH*	*DTCH*	*DTCH*	*DTCH*	*DTCH*
RLGD	0.1751***	0.1930***	0.1919***	0.1660***	0.1676***
	(0.0483)	(0.0474)	(0.0470)	(0.0461)	(0.0461)
PGDP		-0.2185***	-0.2469***	-0.2680***	-0.2747***
		(0.0471)	(0.0631)	(0.0632)	(0.0637)
PFDI		-1.3371***	-1.4430***	-1.3081***	-1.2962***
		(0.3630)	(0.3804)	(0.3682)	(0.3677)
INSR		-0.1078***	-0.1164***	-0.1139***	-0.1157***
		(0.0374)	(0.0389)	(0.0352)	(0.0354)
FSIZ			-0.2282***	-0.1473**	-0.1193
			(0.0864)	(0.0737)	(0.0735)
FIND			-0.2788	-0.3623	-0.3708
			(0.4938)	(0.4721)	(0.4702)
RDEV				0.1198***	0.1194***
				(0.0226)	(0.0226)
GOVN					-0.0760*
					(0.0432)
Annual Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.1261	0.1442	0.1485	0.1816	0.1830
N	279	279	279	279	279

Note: * *, *, and * represent significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors of double clustering are listed in parentheses.

(1) Key explanatory variables. Analyzing columns (1)-(5) of Table 3 reveals that the coefficients associated with red culture continuity (RLGD) are consistently and significantly positive at the 1% significance level. This indicates that as the strength of red culture continuity increases, there is a notable improvement in the level of big data technology innovation. The findings from the baseline regression results strongly support the hypothesis posited in this paper, highlighting the positive influence of sustained red culture on promoting big data technology innovation.

(2) Control variables. Examining column (5) of Table 3 reveals several significant findings. Firstly, the coefficient of economic development (PGDP) exhibits a significant negative

relationship at the 1% significance level. This could be attributed to the notion that as economies progress and develop, market demand increases while firms' profitability improves. Consequently, this could diminish the incentive for innovation, thus affecting the level of big data technology innovation.

Secondly, the coefficient of foreign direct investment (PFDI) also demonstrates a significant negative association at the 1% significance level. Existing research suggests that FDI may not necessarily foster increased incentives for enterprises to innovate in science and technology and could even be detrimental to overall technological innovation (Jiang and Xia, 2005). As a result, the presence of FDI in the context of big data technology innovation may lead to a reduction in the overall level of technological innovation.

Thirdly, the coefficient of the level of industrial structure (INSR) displays a significant negative relationship at the 1% significance level. This could be attributed to the observation that China's digital transformation exhibits a pattern where the tertiary industry takes the lead, followed by the secondary industry, while the primary industry lags (Chen, Zhang, and Wu 2020). Consequently, upgrading the industrial structure increases the demand for digital talent, potentially crowding out talent resources for big data technology innovation.

Fourthly, the coefficient of research and development investment (RDEV) exhibits a significant positive relationship at the 1% significance level. This aligns with the understanding that technical talents drive technological innovation (Bian, Wu, and Bai 2019). Therefore, increased investment in research and development is likely to positively impact big data technological innovation.

The remaining variables do not require further repetition in this context.

3.3 Robustness Tests

The coefficients of the key explanatory variables in columns (1)-(5) of Table 3 exhibit significant results at the 1% significance level, highlighting their robustness. These findings serve as an initial robustness test for the proposed hypotheses. However, to further strengthen the validity of the results, additional robustness tests will be conducted in this paper. These tests will address potential endogeneity concerns, substituting the explanatory variables, replacing the key explanatory variables, and introducing additional control variables. These additional analyses aim to enhance the reliability and robustness of the findings by examining the stability of the relationships under different specifications and controlling for potential confounding factors.

(1) Endogenous treatment. The empirical findings demonstrate that the continuity of red culture plays a facilitative role in fostering big data technology innovation. On the other hand, the influence of big data technology innovation on the continuity of red culture appears to be less significant. As a result, establishing a two-way causal relationship between the two variables becomes challenging. However, it is important to acknowledge that the strength of red culture continuity (*RLGD*) might still be affected by endogeneity issues arising from measurement errors and other factors.

To address this potential endogeneity, this paper adopts the approach suggested by Chen and Zhang (2021) and Chen, Yan, and Chen (2022), utilizing the mean value of the strength of red culture continuity in other cities during the same year (*ivRLGD*) as an instrumental variable. Moreover, considering that the measurement of red culture strength in other cities may also be subject to measurement errors, *ivRLGD* is expected to be correlated with RLGD, meeting the correlation requirement for instrumental variables. The instrumental variables method (IV) is employed to re-estimate Equation (1), where *DTCH* serves as the explanatory variable and *RLGD* as the key explanatory variable.

To assess the strength of the instrumental variables, the Cragg-Donald Wald F-statistic is computed for the weak instrumental variables test. The obtained value of 516.947 greatly surpasses the critical value of 16.38, even under a 10% bias. Consequently, *ivRLGD* successfully passes the weak instrumental variables test, confirming its suitability for addressing potential endogeneity concerns.

By employing the instrumental variable (IV) approach, equation (1) was re-estimated using *DTCH* as the explanatory variable and *ivRLGD* as the instrumental variable. The estimation results are presented in column (1) of Table 4. Notably, in column (1), the coefficient associated with the strength of red culture continuity (*RLGD*) exhibits a significantly positive relationship at the 1% significance level. Consequently, when endogeneity concerns are adequately addressed, the findings reinforce the notion that the continuity of the red bloodline positively impacts big data technology innovation. Thus, the research hypothesis remains valid.

Table 4. Robustness test of Equation (1)

	(1)	(2)	(3)	(4)	(5)
Variables	*DTCH*	*rDTCH*	*DTCH*	*DTCH*	*DTCH*
RLGD	0.3456***	0.0311***			0.1357***
	(0.1288)	(0.0084)			(0.0374)
rRLGD			0.0355***		
			(0.0082)		
rrRLGD				0.7409***	
				(0.1601)	
FTCH					0.1632**
					(0.0747)
CTCH					0.0944***
					(0.0122)
Annual Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.2272	0.2890	0.2298	0.2396	0.5514
N	279	279	279	279	279

Note: * *, *, and * represent significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors of double clustering are listed in parentheses.

(2) Substitution of dependent variables. Equation (1) is re-estimated using fixed effects (FE), with *rDTCH* as the explanatory variable. The results of this estimation are presented in column (2) of Table 4. Remarkably, the findings from column (2) reaffirm the robustness of the conclusion that the continuity of red culture is advantageous for big data technology innovation. Moreover, this robustness holds even when the dependent variables are replaced. Therefore, the research hypothesis remains valid and well-supported by the evidence.

(3) Substitution of key independent variables. Equation (1) is re-estimated using fixed effects (FE), employing *rRLGD* and *rrRLGD* as the key explanatory variables separately. The results of these estimations are presented in columns (3) and (4) of Table 4. Notably, the findings from columns (3) and (4) further strengthen the conclusion that the continuation of red culture contributes positively to big data technology innovation. Moreover, this robustness is evident even when the key independent variables are replaced. Therefore, the research hypothesis remains well-supported by the evidence, underscoring the beneficial relationship between red culture continuity and big data technology innovation.

(4) Adding control variables. Further analysis reveals that both fintech development and technology innovation have an equally positive impact on big data technology innovation. As a result, these two variables are employed as mediating variables in this study rather than control variables. To investigate the combined influence of red culture continuity, financial technology (*FTCH*), and science and technology innovation (*CTCH*), equation (1) is re-estimated, and the results are presented in column (5) of Table 4. Remarkably, column (5) reaffirms the robustness of the conclusion that the continuation of red culture fosters technological innovation in big data. Moreover, the research hypothesis remains valid and well-supported by the evidence. Therefore, the findings underscore the favorable

relationship between red culture continuity and big data technology innovation, even when considering the presence of *FTCH* and *CTCH* as additional factors.

4. Mechanism research

In this section, we aim to differentiate between corporate innovation in the financial and real sectors regarding the impact of red culture continuity. This distinction allows us to conduct a mechanism analysis, which helps us understand how the continuation of red culture facilitates corporate innovation. Subsequently, we proceed to test these mechanisms empirically.

4.1 Mechanism Analysis

As previously discussed, fostering a culture of innovation within the financial sector contributes to corporate innovation, particularly in financial innovation. Since the global financial crisis in 2008, the financial sector has been leveraging digital technologies such as big data and artificial intelligence to innovate products, processes, and business models, leading to the emergence of fintech innovation. Consequently, maintaining a culture of innovation within the financial sector not only supports fintech advancement but also encourages regional fintech development. Furthermore, this ecosystem can stimulate innovation in big data technology for several reasons.

Firstly, the demand for big data technology serves as a driving force. Big data technology ranks among the top five drivers of fintech innovation (Chen, Yan, and Chen 2021). As the financial sector continues integrating big data and other technologies into financial operations, the demand for big data technology naturally increases. Over time, as financial technology continues to evolve, the need for big data technology will progressively grow, fueling innovation in this field.

Secondly, fostering big data technology innovation helps mitigate information asymmetry. China's financial system is predominantly bank-centric, with banking institutions as the primary source of external financing for Chinese enterprises (Chen, Li, and Wang 2011). However, the inherent information asymmetry between banks and enterprises poses challenges in effective risk management during lending processes. This makes banks cautious in lending practices, resulting in financing constraints for Chinese enterprises, including those engaged in big data technology innovation. The development of fintech expands information sharing within the credit market, reducing the cost of information screening and monitoring through a rich dataset of loan information. Consequently, this reduces the information asymmetry between banks and enterprises (Jin, Li, and Liu 2020; Sheng and Fan 2020), alleviating financing constraints and providing financial support for enterprises implementing big data technology innovation.

Thirdly, fintech development influences banks' risk appetite. The advancement of fintech fosters a form of disguised interest rate marketization, reshaping banks' liability structures. Banks become more reliant on wholesale funding, such as interbank lending, resulting in higher costs on their liability side. To compensate for potential losses, banks are compelled to allocate their resources to higher-risk assets, thereby increasing their risk-taking behavior (Qiu, Huang, and Ji 2018). This shift in risk-taking by banks also helps alleviate financing constraints for enterprises, further facilitating financial support for implementing big data technology innovation.

To conclude, by promoting enterprise innovation, the continuation of a culture of innovation in the financial sector facilitates fintech development, which, in turn, drives innovation in big data technology. Therefore, it can be observed that fostering a culture of innovation has significant fintech effects (Figure 1).

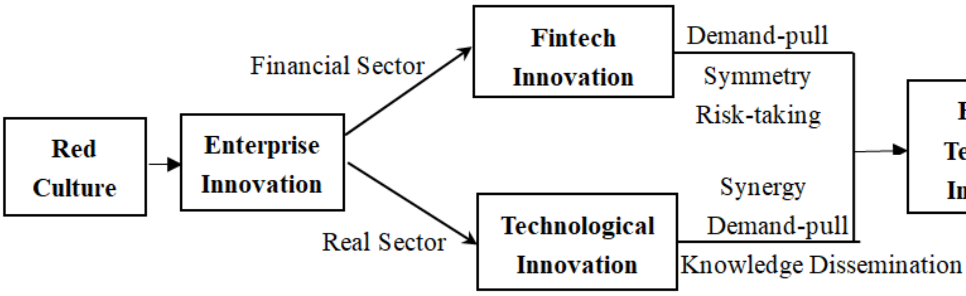

Figure 1. The influence mechanism of red culture on big data technology innovation

Continuing the legacy of innovation facilitates corporate advancement, not limited to big data technology but encompassing a wide array of technological innovations in the real sector. Therefore, perpetuating an innovation-driven culture promotes enterprise innovation in the real sector, ultimately leading to macroscopic improvements in regional science and technology innovation. Enhancing the level of regional science and technology innovation, in turn, catalyzes the advancement of big data technology innovation. This mechanism can be attributed to two key factors.

Firstly, the synergy effect plays a pivotal role. To maintain a sustainable competitive advantage, physical enterprises must continually engage in science and technology innovation. However, enterprises often lack the knowledge and technology required for innovation, creating a strong synergy and complementary relationship between internal research and development (R&D) activities and external knowledge acquisition. Consequently, knowledge and technology sharing among enterprises become a vital avenue for promoting technological innovation (Zhang and Du 2007). In the context of big data technology innovation, digital technologies such as artificial intelligence provide robust algorithmic support for processing large volumes of data. A strong synergistic and complementary relationship exists between these digital technologies and big data technology innovation, enabling enterprises to concentrate their resources, technologies, and efforts on driving advancements in big data technology. A similar synergistic and complementary relationship exists between big data technology innovation and other technological innovations, such as information technology. Hence, regions with higher levels of science and technology innovation are more likely to create synergies and complementary relationships with big data technology innovation, thereby facilitating its advancement.

Secondly, the demand-pull factor plays a crucial role. An increase in the level of regional innovation signifies a higher investment in innovation by enterprises within the region. This, in turn, leads to the emergence of new products and models, intensifying industry competition (Chen and Zhang 2021). To cope with such competition, firms are compelled to strengthen their innovation efforts. Since 2008, there has been a growing trend among physical enterprises to undertake comprehensive, end-to-end digital transformation innovation based on digital technologies like big data and artificial intelligence (Chen, Zhang, and Wu 2020). Consequently, digital transformation innovation has become a strategic imperative for enterprises to navigate industry competition. In pursuing digital transformation innovation, enterprises naturally increase their demand for digital technologies, including big data, thereby driving regional big data technology innovation.

Thirdly, knowledge dissemination plays a vital role. Knowledge accumulation is a prerequisite for enterprise innovation, and sharing knowledge facilitates the expansion of enterprises' knowledge base, thereby augmenting their knowledge accumulation (Li et al. 2015). As the regional science and technology innovation level improves, innovators in science and technology gradually gather, leading to more convenient and frequent face-to-face communication among them. This facilitates the swift dissemination of knowledge and information relevant to big data technology innovation, thereby fostering an environment conducive to knowledge dissemination in big data innovation.

Consequently, this process bolsters the knowledge accumulation related to enterprise big data technology innovation, ultimately propelling advancements in big data technology innovation.

In conclusion, perpetuating a culture of innovation not only drives enterprise innovation in the real sector but also fuels regional science and technology innovation. The interplay between the synergy effect, demand-pull, and knowledge dissemination mechanisms facilitates the advancement of big data technology innovation as Figure 1 shows.

4.2 Mechanism Test

In this study, we employ the test procedure proposed by Wen and Ye (2014) while referring to the work of Chen and Zhang (2021) to establish the model for testing the proposed mechanism.

$$DTCH_{it} = \alpha_0 + \beta_1 * RLGD_{it} + \eta * \boldsymbol{X} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$M_{it} = \alpha_0 + \xi * RLGD_{it} + \eta * \boldsymbol{X_1} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$DTCH_{it} = \alpha_0 + \beta_1 * RLGD_{it} + \delta * M_{it} + \eta * \boldsymbol{X} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (4)$$

In the aforementioned model, the mediating variable is denoted as M_{it}, representing both the level of financial technology (*FTCH*) and technological innovation (*CTCH*). In relation to the level of financial technology (*FTCH*), this study adopts the methodology employed in previous literature (e.g., Qiu, Huang, and Ji 2018) and utilizes the Beijing University Digital Inclusive Finance Composite Index for each city as an indicator of the level of financial technology. To maintain uniformity in the scale, the *FTCH* is obtained by dividing the Beijing University Digital Inclusive Finance Composite Index by 100.

Regarding the level of *CTCH*, this study follows the approach outlined by Lu, Yang, and Ma (2021). The *CTCH* is determined by subtracting the number of patent applications for big data technology from the total number of patent applications for each city and then dividing this value by the total population. This proxy variable serves as an indicator of the level of technology innovation.

Thus, in the model, A represents the mediating variable encompassing the *FTCH* and *CTCH*, with the *FTCH* derived from the Beijing University Digital Inclusive Finance Composite Index scaled down by dividing by 100. The *CTCH*, conversely, is obtained by subtracting the number of patent applications for big data technology from the total number of patent applications for each city, divided by the total population, serving as a proxy for the level of science and technology innovation.

The test procedure is as follows: Firstly, Equation (2) is estimated without including mediating variables. If the coefficient of $RLGD_{it}$ is found to be significant, it indicates that the continuity of the red bloodline has a direct effect on the technological innovation of big data. In such cases, further analysis is conducted. Conversely, if the coefficient is insignificant, it suggests a potential masking effect. Secondly, the regression of Equation (3) is performed to examine the effect of $RLGD_{it}$ on the mediating variables M_{it}. The significance of the coefficient ξ in Equation (3) and δ in Equation (4) is assessed. If both coefficients are significant, it signifies the presence of a mediating effect. Furthermore, if only one of the coefficients, either ξ in Equation (3) or δ in Equation (4), is significant, the mediating effect is then tested using the Sobel test.

In Equation (2) and Equation (4), $\boldsymbol{X}$ represents the control variables, which are consistent with those in Equation (1). Additionally, in Equation (3), $\boldsymbol{X_1}$ is the control variable. When utilizing the level of financial technology as the explanatory variable, this study incorporates various control variables based on relevant literature examining financial technology and technological innovation (e.g., Chen, Yan, and Chen 2022; Bian, Wu, and Bai 2019; Li and Yang 2019). These control variables include the level of economic development, foreign direct investment, the level of industrial structure, the level of financial development, financial decentralization, R&D investment, government intervention, and financial talent (*FEMP*), which is represented by the natural logarithm of the number of financial employees.

Furthermore, when the level of science and technology innovation is employed as the explanatory variable, this study refers to literature on science and technology innovation (e.g., Bian, Wu, and Bai 2019; Li and Yang, 2019) to determine the control variables. These control variables encompass the level of economic development, foreign direct investment, the level of industrial structure, the level of financial development, financial decentralization, R&D investment, government intervention, and the level of human capital, which is represented by the ratio of the number of college students to the total population. To ensure robustness in the analysis, these control variables are incorporated to account for their potential influence on the relationship between the variables under investigation.

(1) Fintech effect. Equations (2)-(4) are estimated with the *FTCH* as the mediating variable, and the results are presented in columns (1)-(3) of Table 5, Panel A. In column (1), the coefficient of *RLGD* is significant at a 1% level of significance, indicating the presence of an aggregate effect. Similarly, in column (2) of Table 5, Panel A, the coefficient of *RLGD* is significant at a 1% significance level, and in column (3), the coefficient of the mediating variable, *FTCH*, is also significant at a 1% level of significance. Therefore, a financial technology effect is observed. The sign and significance of the combined *RLGD* and *FTCH* demonstrate that continuing the red culture enhances financial technology, thus promoting technological innovation in big data.

In estimating equation (3), it may be challenging for FinTech to influence the continuation of the red culture, and establishing a two-way causality is difficult. However, it is also plausible that *RLGD* is endogenous due to measurement error or other factors. To address this, equation (3) is re-estimated using instrumental variables (IV), with *ivRLGD* as the instrumental variable. The results are presented in column (4) of Panel A in Table 5. Furthermore, as indicated in column (3) of Table 5, Panel A, FinTech contributes to big data technology innovation.

Conversely, big data technology is recognized as one of the drivers of FinTech (Chen, Yan, and Chen 2022), and innovation in big data technology benefits FinTech development. Thus, a two-way causal relationship is established between big data technology innovation and FinTech, rendering the level of FinTech endogenous. Following a similar approach, the instrumental variable *ivFTCH*, representing the mean value of the FinTech level in other cities during the same year, is utilized alongside *ivRLGD*. Equation (4) is then re-estimated using IV, and the results are presented in column (5) of Panel A in Table 5. From columns (4) and (5) of Table 5, Panel A, it can be observed that the conclusion regarding FinTech effects remains robust even after accounting for endogeneity.

Re-estimating Equations (2)-(4) with *rDTCH* as the explanatory variable yields the results presented in Table 5, Panel B. Re-estimating Equations (2)-(4) with *rRLGD* and *rrRLGD* as the primary explanatory variables, respectively, results in Table 5, Panel C and Panel D. Panel B, Panel C, and Panel D all support the conclusion that continuing the red culture improves FinTech, which subsequently benefits big data technology innovation. Hence, the assertion of the existence of FinTech effects remains robust.

Table 5. Estimation Results of Fintech Effects

Panel A					
	(1)	(2)	(3)	(4)	(5)
Variables	*DTCH*	*FTCH*	*DTCH*	*FTCH*	*DTCH*
RLGD	0.1878***	0.0651***	0.1571***	0.0809***	0.2765**
	(0.0452)	(0.0102)	(0.0430)	(0.0242)	(0.1160)
FTCH			0.4711***		0.8521***
			(0.0891)		(0.1452)
Annual Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.2343	0.9952	0.2494	0.9952	0.2336
N	279	279	279	279	279
Panel B					

	(1)	(2)	(3)	(4)	(5)
Variables	*rDTCH*	*FTCH*	*rDTCH*	*FTCH*	*rDTCH*
RLGD	0.0311***	0.0651***	0.0252***	0.0809***	0.0540**
	(0.0084)	(0.0102)	(0.0081)	(0.0242)	(0.0255)
FTCH			0.0914***		0.1548***
			(0.0138)		(0.0216)
Annual Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.2890	0.9952	0.3071	0.9952	0.2886
N	279	279	279	279	279
Panel C					
	(1)	(2)	(3)	(4)	(5)
Variables	*DTCH*	*FTCH*	*DTCH*	*FTCH*	*DTCH*
rRLGD	0.0355***	0.0153***	0.0281***	0.0395***	0.1370*
	(0.0082)	(0.0027)	(0.0077)	(0.0153)	(0.0713)
FTCH			0.4859***		0.7954***
			(0.0900)		(0.1581)
Annual Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.2298	0.9952	0.2459	0.9950	0.1828
N	279	279	279	279	279
Panel D					
	(1)	(2)	(3)	(4)	(5)
Variables	*DTCH*	*FTCH*	*DTCH*	*FTCH*	*DTCH*
rrRLGD	0.7409***	0.2227***	0.6395***	0.2777***	0.9528**
	(0.1601)	(0.0340)	(0.1537)	(0.0837)	(0.4016)
FTCH			0.4558***		0.8319***
			(0.0889)		(0.1465)
Annual Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.2396	0.9952	0.2537	0.9952	0.2397
N	279	279	279	279	279

Note: The instrumental variables passed the validity test, the same as follows.

(2) Technology innovation effect. Equations (2)-(4) were estimated using *CTCH* as the mediating variable, and the results are presented in columns (1)-(3) of Table 6, Panel A. From these columns, it is evident that the science and technology innovation effect exists. The sign and significance of *RLGD* and *CTCH* demonstrate that continuing red culture enhances technology innovation, thereby promoting big data technology innovation.

In estimating Equation (3), it may be challenging for science and technology innovation to influence the continuation of red culture, and establishing a two-way causality is difficult. It is also possible that *RLGD* is endogenous due to measurement error. Following the previous approach, Equation (3) is re-estimated using IV, with *ivRLGD* as the instrumental variable. The results are presented in column (4) of Panel A in Table 6. Additionally, column (3) of Table 6, Panel A, highlights the promotion of technological innovation in big data by technology innovation.

Moreover, applying digital technologies such as big data accelerates information flow, enabling enterprises to acquire knowledge and technologies at a lower cost. This leads to an increase in their knowledge stock, facilitating the accumulation of sufficient knowledge for innovation (Xu, Hou, and Cheng 2022). Consequently, big data technologies can also benefit science and technology innovation, establishing a two-way causal relationship between big data technology innovation and technology innovation, rendering the level of technology innovation endogenous. Following a similar approach, the instrumental variable *ivCTCH*, representing the mean value of the *CTCH* for the same year in other cities, is used alongside *ivRLGD* to re-estimate Equation (4) using IV. The results are presented in column (5) of Panel A in Table 6. From columns (4) and (5) of Table 6, Panel A, it is evident that the conclusion regarding the existence of the science and technology innovation effect remains robust, even after accounting for endogeneity.

Applying the same approach as the FinTech effect, Panel B, Panel C, and Panel D are obtained, reaffirming that the continuation of red culture improves science and technology innovation, subsequently benefiting big data technology innovation. Hence, the conclusion that the science and technology innovation effect exist remains robust.

Table 6. Estimation Results of Technology Innovation Effect

Panel A					
	(1)	(2)	(3)	(4)	(5)
Variables	*DTCH*	*CTCH*	*DTCH*	*CTCH*	*DTCH*
RLGD	0.1878***	0.4340**	0.1459***	0.8382***	0.2499**
	(0.0452)	(0.1887)	(0.0389)	(0.3174)	(0.1093)
CTCH			0.0954***		0.1171***
			(0.0120)		(0.0143)
Annual Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.2343	0.3363	0.5497	0.3354	0.5298
N	279	279	279	279	279
Panel B					
	(1)	(2)	(3)	(4)	(5)
Variables	*rDTCH*	*CTCH*	*rDTCH*	*CTCH*	*rDTCH*
RLGD	0.0311***	0.4340**	0.0245***	0.8382***	0.0516**
	(0.0084)	(0.1887)	(0.0072)	(0.3174)	(0.0247)
CTCH			0.0150***		0.0183***
			(0.0023)		(0.0027)
Annual Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.2890	0.3363	0.5381	0.3354	0.5191
N	279	279	279	279	279
Panel C					
	(1)	(2)	(3)	(4)	(5)
Variables	*DTCH*	*CTCH*	*DTCH*	*CTCH*	*DTCH*
rRLGD	0.0355***	0.2109***	0.0148**	0.4080**	0.1222*
	(0.0082)	(0.0507)	(0.0063)	(0.1846)	(0.0653)
CTCH			0.0956***		0.1160***

			(0.0120)		(0.0144)
Annual Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.2298	0.3390	0.5446	0.3357	0.4754
N	279	279	279	279	279
Panel D					
	(1)	(2)	(3)	(4)	(5)
Variables	*DTCH*	*CTCH*	*DTCH*	*CTCH*	*DTCH*
rrRLGD	0.7409***	2.8811***	0.4790***	2.8747***	0.8603**
	(0.1601)	(0.6672)	(0.1377)	(1.0910)	(0.3781)
CTCH			0.0949***		0.1155***
			(0.0121)		(0.0144)
Annual Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	2,298	2,298	2,298	2,298	2,298
R-squared	0.2396	0.3397	0.5500	0.3397	0.5299
N	279	279	279	279	279

5. Conclusion and Implications

How does the continuation of red culture impact big data technology innovation? This paper conducts an empirical investigation using data from Chinese cities between 2011 and 2019 to explore the influence of continuing red culture on big data technology innovation and its underlying mechanism. The findings reveal the following:

Firstly, continuing red culture fosters employees' positive psychological capital and psychological ownership of the enterprise. Both factors contribute to enterprise innovation, thereby promoting big data technology innovation. The results indicate that cities with a stronger continuation of red culture exhibit higher levels of big data technology innovation.

Secondly, promoting enterprise innovation driven by continuing red culture has distinct effects in different sectors. In the financial sector, continuing red culture facilitates financial technology innovation, while in the real sector, it promotes technological innovation among real enterprises. As a result, it propels the development of regional financial technology and enhances the level of regional technological innovation. The development of financial technology helps advance big data technology innovation by reducing information asymmetry between banks and enterprises, enhancing banks' risk-taking capabilities, and increasing the demand for big data technology. Similarly, regional science and technology innovation stimulates big data technology innovation through synergistic effects, knowledge dissemination, and the growing demand for big data technology in digital transformation.

In summary, this study demonstrates that the continuation of red culture positively influences big data technology innovation. By fostering positive psychological factors and promoting innovation in different sectors, continuing red culture contributes to advancing regional financial technology and technological innovation. The findings underscore the importance of cultural factors in shaping the landscape of big data technology innovation.

The findings of this paper carry significant implications:

Firstly, continuing red culture emerges as a promoter of big data technology innovation. Big data represents a valuable resource in industrial society and those who harness its potential gain a competitive advantage. By fostering technological innovation in big data, continuing red culture serves a dual purpose. It not only allows party members and cadres to learn from history, gain confidence, uphold moral values, and take action but also holds strong economic significance. By promoting regional innovation in big data technology through the continuation of red culture, local areas can effectively leverage their big data resources to drive the development of the digital economy. This, in turn, fuels the growth of the local economy, providing new impetus for its high-quality development. Consequently, government departments are encouraged to enhance their enthusiasm and proactiveness in continuing the red culture.

Secondly, continuing red culture facilitates big data technology innovation by driving the development of financial technology and technological innovation. Fintech represents a focal point in the global financial competition and reshapes financial systems worldwide. In January 2022, the People's Bank of China issued the "Financial Technology Development Plan (2022-2025)", outlining key tasks in eight areas. Local governments play a crucial role in implementing this plan. Continuing the red culture can encourage financial institutions to actively embrace fintech innovation, thereby propelling the development of financial technology. Consequently, continuing red culture is important for fostering local fintech growth. Simultaneously, technological innovation is a decisive factor in a nation's comprehensive power and plays a leading role in economic development. It acts as an inexhaustible driving force for China's high-quality economic progress. By promoting the continuation of red culture, the level of regional science and technology innovation can be elevated. Therefore, beyond traditional financial subsidies, local governments can actively promote local science and technology innovation by conducting various activities centered around continuing red culture.

Thirdly, the underlying mechanism through which continuing red culture promotes big data technology innovation is its ability to enhance employees' self-confidence, hope, optimism, resilience, and positive psychological capital. By fostering a sense of belonging, creating a supportive work environment, nurturing a sense of accomplishment, and instilling self-efficacy, employees' psychological ownership of the company is strengthened. The positive psychological capital and psychological ownership of employees are pivotal not only for fostering corporate innovation but also for reducing agency costs and mitigating conflicts within the organization. This, in turn, enhances corporate output and improves overall performance. Therefore, the benefits of continuing red culture are not limited to party members and cadres alone but can be extended to all employees within state-owned and private enterprises. Enterprises can incorporate the continuation of red culture into their corporate culture and, through ongoing activities focused on red culture, continuously reinforce employees' positive psychological capital and psychological ownership of the enterprise, thereby yielding positive outcomes.

Reference:

1. Avey, J. B., T. S. Wernsing, and M. E. Palanski. 2012. "Exploring the process of ethical leadership: The mediating role of employee voice and psychological ownership ." *Journal of Business Ethics*, 107:21-34. https://doi.org/10.1007/s10551-012-1298-2
2. Belk, R. W. 1988. "Possessions and the extended self." *Journal of Consumer Research* ,15 (2):139-168. https://doi.org/10.1086/20915 4
3. Bian, Y.C., L.H. Wu, and J.H. Bai. 2019. "Does high-speed rail improve regional innovation in China?" *Journal of Financial Research*, 468(6): 132-149.
4. Cao, J.S. 2021. "The logical necessity and practical consciousness of inheriting the red gene in the new era." *Nanjing Journal of Social Sciences*, 404(6): 9-17. https://doi.org /10.15937/j.cnki.issn1001-8263.2021.06.002.
5. Chen, C.W., and L.P. Huang. 2021. "Theoretical logic and practice way of assimilating red gene into grassroots social governance." *Gansu Social Sciences*, 254(5): 9-15. https://doi.org/10.15891/j.cnki.cn62-10 93/c.2021.05.003.
6. Chen, D.Q., S.F. Li, and C. Wang. 2011. "The government quality, the ultimate ownership and the corporate cash holdings." *Journal of Management World*, 218(11): 127-141. https:// doi.org/10.19744/j.cnki.11-1235/f.2011.11.01 2.
7. Chen, H., and Q.S. Hui. 2012. "On employees' innovative working behavior from the perspective of social exchange: The mediator role of psychological ownership." *Contemporary Finance & Economics*, 331(6): 69-79.

8. Chen, X., D. Yan, and W. Chen. 2022. "Can the digital economy promote FinTech development?" *Growth and Change*, 53(1): 221-247. https://doi.org/10.1111/grow.12582
9. Chen, X.D. 2001. "Be a revolutionary optimist ." *Qiushi*, 23: 60.
10. Chen, X.H., and H.W. Zhang. 2021. "How does the digital economy affect the level of enterprise risk-taking?" *Business and Management Journal*, 43(5): 93-108. https://doi.org/10.19616/j.cnki.bmj.2021.05.006.
11. Chen, X.H., H.W. Zhang, and Y.C. Wu. 2020. "How does digital economy affect the level of industrial structure?" *Securities Market Herald*, 336(7): 20-29.
12. Dai, W.L., L. Su, and J.P. Yang. 2020. "The relationship among psychological ownership, knowledge sharing and innovative behavior of team members: The multilevel moderating effect of coworker trust." *Science Research Management*, 41(12): 246-256. https://doi.org/10. 19571/j.cnki.1000-2995.2020.12.023
13. Doh, S., and B. Kim. 2014. "Government support for SME innovations in the regional industries: The case of government financial support program in South Korea." *Research Policy*, 43(9):1557-1569. https://doi.org/10.1016/j.respol.2014.05.001.
14. Fu, M.W., J.Y. Ye, Y.X. Meng, and Z. Lei. 2015. "The impacts of domestic content protection on indigenous innovation—Evidence from China's wind power technology industry." *Economic Research Journal*, 50(2): 118-131.
15. Furby, L. 1978. "Possession in humans: An exploratory study of its meaning and motivation." *Social Behavior and Personality: An International Journal*, 6(1): 49-65. https://doi.org/10.2224/sbp.1978.6.1.49
16. Gist, M. E., and T. R. Mitchell. 1992. "Self-efficacy: A theoretical analysis of its determinants and malleability." *Academy of Management Review*, 17(2): 183-211. https://doi.org/10.5465/amr.1992.4279530
17. Gu, L., C.C. Lyu, and J.P. Yang. 2019. "The influence of social capital on the innovation output and entrepreneurship level in the West China." *Journal of Management*, 32(3): 31-40. https://doi.org/10.19808/j.cnki.41-1408/f.2019.03.004.
18. Guo, D., Y. Guo, and K. Jiang. 2016. "Government-subsidized R&D and firm innovation: Evidence from China." *Research Policy*, 45(6): 1129-1144. https://doi.org/10.1016/j.respol.2016.03.002.
19. Jiang, D.C., and L.K. Xia. 2005. "The empirical study of the function of FDI on innovation in China's high-tech industries." *The Journal of World Economy*, 8: 5-12.
20. Jin, H.F., H.J. Li, and Y.L. Liu. 2020. "FinTech, banking risks and market crowding-out effect." *Journal of Finance and Economics*, 46(5): 52-65. https://doi.org/10.16 538/j.cnki.jfe.2020.05.004.
21. Keller, W. 2002. "Geographic localization of international technology diffusion." *American Economic Review*, 92(1): 120-142. https://doi.org/10.1257/000282802760015630
22. Li, J. 2019. "Moral education value and practical logic of regional red educational resources in classroom." *Journal of the Chinese Society of Education*, 320(12): 72-75.
23. Li, J., Yuan, L., L. Ning, and J. Li-Ying. 2015. "Knowledge sharing and affective commitment: the mediating role of psychological ownership." *Journal of Knowledge Management*, 19(6): 1146-1166. https://doi.org/10.1108/JKM-01-2015-0043
24. Li, W.M., Q. Ao, C.Q. Yin, S.Y. Li, L.G. Wang, G.L. Ling, L.X. Pei, Y.X. Liu, and C.H. Guo. 2020. "Driving factors and influencing mechanism of tourists' pro-environmental behavior in Shaoshan red tourism area." *Economic Geography*, 40(11): 233-240. https://doi.org/10.15957/j.cnki.jjdl.2020.11.026
25. Li, Z., and S.Y. Yang. 2019. "Can national high-tech zones raise urban innovation level?" *South China Journal of Economics*, 363(12): 49-67. https://doi.org/10.19592/j.cnki.scje.361822
26. Liu, F., I. H. S. Chow, J. C. Zhang, and M. Huang. 2019. "Organizational innovation climate and individual innovative behavior: exploring the moderating effects of psychological ownership and psychological empowerment." *Review of Managerial Science*, 13:771-789. https://doi.org/10.1007/s11846-017-0263-y
27. Lu, J., and T.T. Li. 2021. "Industrial structure, technological innovation and green total factor productivity: Research in the perspective of heterogeneity." *Chinese Journal of Population Science*, 205(4): 86-97.

28. Lu, J.J., S.Y. Yang, and C. Ma. 2021. "Fiscal decentralization, financial decentralization and technological innovation." *South China Journal of Economics*, 381(6): 36-50. https://doi.org/10.19592/j.cnki.scje.381435.
29. Luthans, F., J. B. Avey, R. Clapp-Smith, and W. Li. 2008. "More evidence on the value of Chinese workers' psychological capital: A potentially unlimited competitive resource?" *The International Journal of Human Resource Management*, 19(5): 818-827. https://doi.org/10.1080/09585190801991194
30. Luthans, F., K. W. Luthans, and B. C. Luthans. 2004. "Positive psychological capital: beyond human and social capital." *Business Horizons*, 47(1): 45-50. https://doi.org/10.1016/j.bushor.2003.11.007
31. Mumford, M. D., G. M. Scott, B. Gaddis, and J. M. Strange. 2002. "Leading creative people: Orchestrating expertise and relationships." *The Leadership Quarterly*, 13(6): 705-750. https://doi.org/10.1016/S1048-9843(02)00158-3
32. Peng, Z.D., and S.Y. Jiang. 2021. "On red gene and its transmission in new era." *Social Sciences in Hunan*, 203(1): 12-20.
33. Pierce, J. L., T. Kostova, and K. T. Dirks. 2001. "Toward a theory of psychological ownership in organizations." *Academy of Management Review*, 26(2): 298-310. https://doi.org/10.5465/amr.2001.4378028
34. Qiu, H., Y.P. Huang, and Y. Ji. 2018. "How does FinTech development affect traditional banking in China? The perspective of online wealth management products." *Journal of Financial Research*, 461(11): 17-29.
35. Romijn, H., and M. Albaladejo. 2002. "Determinants of innovation capability in small electronics and software firms in southeast England." *Research Policy*, 31(7): 1053-1067. https://doi.org/10.1016/S0048-7333(01)00176-7
36. Scott, S. G., and R. A. Bruce. 1994. "Determinants of innovative behavior: A path model of individual innovation in the work-place." *Academy of Management Journal* , 37 (3):580-607. https://doi.org/10.5465/2567 01
37. Sheng, T.X., and C.L. Fan. 2020. "FinTech, optimal banking market structure, and credit supply for SMEs." *Journal of Financial Research*, 480(6): 114-132.
38. Sweetman, D., F. Luthans, J. B. Avey, and B. C. Luthans. 2011. "Relationship between positive psychological capital and creative performance." *Canadian Journal of Administrative Sciences*, 28(1): 4-13. https://doi.org /10.1002/cjas.175
39. Van Dyne, L., and J. L. Pierce. 2004. "Psychological ownership and feelings of possession: Three field studies predicting employee attitudes and organizational citizenship behavior." *Journal of Organizational Behavior*, 25(4): 439-459. https ://doi.org/10.1002/job.249
40. Wen, Z.L., and B.J. Ye. 2014. "Analyses of mediating effects: The development of methods and models." *Advances in Psychological Science*, 22(5): 731-745.
41. Xiong, J.M., M. Hai, F. Huang, L. Xin, and Y. Xu. 2020. "Family cumulative risk and mental health in Chinese adolescents: The compensatory and moderating effects of psychological capital." *Psychological Development and Education*, 36(1): 94-102. https://doi.org/10.16187/j.cnki.issn1001-4918.2020.01.11
42. Xu, L., L.Q. Hou, and G.B. Cheng. 2022. "Innovation effect of national big data comprehensive pilot zone." *Science & Technology Progress and Policy*,39(20): 101-111.
43. Zhang, H. 2011. "Red resources and thesis on the Sinicization, modernization and popularization of Marxism." *Studies on Marxism*, 134(8): 35-41.
44. Zhang, H.Y., and R. Du. 2007. "The operating mechanisms of indigenous innovation alliance based on knowledge sharing." *Studies in Science of Science*, S2: 480-485. https://doi.org/10.16192/j.cnki.1003-2053.2007.s2.019.
45. Zhang, W., and J.H. Quan. 2014. "Analysis on paths of the propagation of red culture of omni media." *Social Sciences in Hunan*, 264(4): 257-260.
46. Zhou, S.Q., and C. Pang. 2019. "Impact of industrial agglomeration and coordinated development on regional technological innovation: An empirical study based on Guangdong-Hong Kong-Macau Greater Bay Area's manufacturing industry, financial industry and education." *Science and Technology Management Research*, 39(19): 104-114.