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Original Paper

Big Data Construction and Shadow Banking of Private Non-Financial Enterprises——Based on the National-level Big Data Comprehensive Pilot Zone Policy

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Abstract

In recent years, more private non-financial enterprises engage in shadow banking activities, causing serious negative effects on corporate operations and the financial system. Meanwhile, to promote big data innovation and development, the Party and government established national comprehensive big data pilot zones to enhance data circulation as a key production factor. From the perspective of big data development, this study takes private non-financial enterprises in national-level big data comprehensive pilot zones at the prefectural level (2012–2022) as samples and employs the PSM-DID method to examine whether big data development affects the shadow banking behavior of non-financial enterprises and explore its underlying mechanisms. The results show that big data development effectively curbs shadow banking activities among private non-financial enterprises, and this finding remains robust across multiple tests. Further analysis reveals that big data construction suppresses such activities by alleviating information asymmetry and enhancing social trust. Heterogeneity analysis indicates that the inhibitory effect is more pronounced in regions with higher economic development levels and among high-tech private non-financial enterprises. This study offers a new research solution for mitigating shadow banking in private non-financial enterprises, effectively reduces financial risks, and holds significant implications for promoting the growth of these enterprises.

Keywords

Big Data Construction, Shadow Basnking, Private Non-Financial Enterprise, National Big Data Comprehensive Pilot Zone

1. Introduction

The shadow banking of non-financial enterprises is a phenomenon that has gradually emerged and developed in recent years. An increasing number of non-financial enterprises are leveraging their own advantages (Xie Yuxin, 2023) to evade formal financial regulation (Cheng Qunrui et al., 2023) and engage in shadow banking activities. According to the "Report on the Shadow Banking Development of Non-Financial Enterprises in China" released in 2023, by the end of 2022, the scale of shadow banking activities among non-financial enterprises in China had reached 40 trillion yuan, accounting for 33% of the total shadow banking volume and 36% of GDP. This scale and impact continue to grow steadily. The unrestricted growth of shadow banking by non-financial enterprises may have considerable adverse impacts on both the corporate activities and the financial system. On the one hand, when these private non-financial enterprises participate in shadow banking, it decreases their investment in innovation, impedes the enhancement of total factor productivity (Luo Jia et al., 2023), promotes a transfer from real economic activities to virtual ones, and increases the financial risks for businesses (Li Jianjun et al., 2019). On the other hand, the shadow banking actions of non-financial enterprises might raise the leverage, complexity and ambiguity within the financial system, thus making it more fragile and susceptible to disturbances. Moreover, regulatory arbitrage and conflicts cause market disorder and make financial markets hard to control (Liu Yuanyuan et al., 2023). Meanwhile, for the implementation of national regional development policies, the Party and government have established national big data comprehensive pilot zones to promote the circulation of data elements and accelerate the development of China's big data industry. At the same time, the Third Plenary Session of the 20th CPC Central Committee put forward 'to improve the systems for the comprehensive integration of the real economy and the digital economy', highlighting the establishment and management of national data infrastructure to accelerate data exchange. In this context, this paper investigates whether the big data advancement can efficiently prevent the shadow banking behaviors of private non-financial enterprises, thus protecting the expansion of the real economy, promoting reasonable resource distribution among private non-financial institutions, and assisting in the steady and healthy economic growth.

Previous research on the determinants of shadow banking activities mainly focuses on two aspects: internal corporate factors and external corporate factors. From the perspective of internal factors, credit constraints under supply chain relationships (Yan Endian et al., 2021), credit misalignment (Bai Jun, 2022), institutional co-ownership (Huang Danhua et al., 2024), financial technology (Sun Jiguo, 2023), and executives' financial backgrounds (Hu Jinyan et al., 2022) affect a firm's involvement in shadow banking. As for external factors, economic uncertainty (Gao Jiechao et al., 2020) and capital market openness (Huang Xianhuan et al., 2021), banking competition (Si Dengkui, 2021), interest rate liberalization for loans (Sun Zhihong et al., 2022), "structural" deleveraging policies (Dou Wei et al., 2022), financing constraints (Cheng Qunrui et al., 2023), and social capital (Liu Lin et al., 2022) also significantly affect firms' shadow banking activities.In the above exploration of the factors leading to shadow banking, no research has been conducted on the relationship between the important external environmental factor of big data construction and the shadow banking of private non-financial enterprises. Therefore, we cannot determine whether big data construction can truly curb the “shadow banking” of private non-financial enterprises. At the same time, in recent years, the country has attached great importance to big data construction and has continuously introduced relevant policies. In view of this, this paper adopts the PSM-DID method, based on the policies of the national-level big data comprehensive experimental zone, and focuses on examining the relationship and influencing mechanism between big data construction and the “shadow banking” of private non-financial enterprises. This paper collects and analyzes the data of private non-financial enterprises in the national-level big data comprehensive experimental zone - the prefecture-level city version (from 2012 to 2022), systematically examines the impact of big data construction on the shadow banking of private non-financial enterprises, and further explores its specific mechanism. The research results show that big data construction significantly inhibits the shadow banking of private non-financial enterprises. After excluding some special samples and conducting robust tests using counterfactual and PSM-DID methods, this conclusion still holds. The paper further examines the mediating effect of information asymmetry and social trust level, and finds that information asymmetry and social trust level are two important paths through which big data construction affects the shadow bankingization of private non-financial enterprises. At the same time, the heterogeneity results indicate that the inhibitory effect of big data construction on the shadow bankingization of private non-financial enterprises in regions with higher economic development levels and those of high-tech type is more obvious.

The main research contributions of this paper are as follows: Firstly, by taking the policies of the national-level big data comprehensive experimental zone as the starting point, it considers the impact of big data construction on the shadow bankingization of private non-financial enterprises, which can reasonably reflect the actual effect of big data construction and make the research conclusion highly persuasive, providing a new perspective for the theoretical research on shadow bankingization. Secondly, from the perspective of the mediation of enterprise information asymmetry and social trust level, this paper examines the mechanism path of big data construction affecting the shadow bankingization of private non-financial enterprises, and discovers that big data construction inhibits the shadow bankingization of private non-financial enterprises by reducing information asymmetry and improving social trust level, providing strong evidence for understanding how big data construction affects the shadow bankingization of non-financial enterprises. Thirdly, through the analysis of regional economic development levels and the heterogeneity of enterprise types, this paper further reveals the relationship between big data construction and the phenomenon of shadow bankingization of private non-financial enterprises, providing effective references and theoretical support for evaluating the policy effect of the national-level big data comprehensive experimental zone and promoting the stable and healthy development of the financial market.

2. Institutional Background and Research Hypotheses

2.1 Institutional Background

In August 2015, the State Council issued the “Action Outline for Promoting the Development of Big Data” (Guo Fa [2015] No. 50), marking that the development of big data has been established as a major national strategy and has been comprehensively planned and deployed. This “Outline” particularly emphasized that by establishing national comprehensive big data experimental zones, with places like Guizhou as examples, the vigorous development of the big data industry would be promoted. This move indicates that the development of big data in Guizhou has officially been incorporated into the national strategic planning.

In March 2016, China’s first national-level comprehensive big data experimental zone was officially approved in Guizhou, marking that this experimental zone will conduct a series of systematic trials and explorations in areas such as data resource management and sharing, data center integration and optimization, and in-depth application of data resources. In October of the same year, the state issued the “Letter on Agreeing to Promote the Construction of National Comprehensive Big Data Experimental Zones in Some Regions” (Document No. 2123 of the Ministry of Development and Reform - High Technology), approving seven regions including the Beijing-Tianjin-Hebei region and the Pearl River Delta region as the second batch of national-level comprehensive big data experimental zones. These regions cover cross-regional types (such as the Beijing-Tianjin-Hebei region, the Pearl River Delta region), regional demonstration types (such as Shanghai, Henan Province, Chongqing City, and Shenyang City), and types of coordinated development of big data infrastructure (such as Inner Mongolia), forming a multi-level and multi-faceted experimental network for big data development.

To ensure that the development of big data can be deeply rooted and effectively benefit the lives of the country and the people, a comprehensive and powerful policy system is urgently needed at all levels, from the highest-level strategic planning to the specific implementation at the local level. The Beijing-Tianjin-Hebei Big Data Comprehensive Pilot Zone has already shown positive results and progress in establishing a tri-city collaborative promotion mechanism, formulating incentive policies for big data industry development, and promoting major projects. Subsequently, Shanghai, Guangdong Province, Inner Mongolia Autonomous Region, Henan Province, etc., have successively issued documents such as “Opinions on the Development of Big Data in Shanghai”, “Action Plan for Promoting the Development of Big Data in Guangdong Province”, “Several Policies for Promoting the Development and Application of Big Data in Inner Mongolia Autonomous Region”, and “Guiding Catalogue for the Development of Big Data Industry in Henan Province”, implementing the relevant standards for big data construction step by step. These measures together constitute an important force for promoting the sustained and healthy development of the big data industry.

2.2 Research Hypothesis

2.2.1 The Impact of Big Data Construction on The Shadow Bankingization of Private Non-financial Enterprises

In April 2011, the Financial Stability Board (FSB) clarified that shadow banking operates as a credit intermediary system that is separate from the banking regulatory system and faces issues of systemic financial risks and regulatory arbitrage. When a large number of industrial enterprises choose shadow banking services and devote most of their energy and time to relying on credit intermediaries such as investment management and trusts for financing and investment, it will lead to the shadow bankingization phenomenon (Li Tiande, 2014). This is bound to cause immeasurable harm to industrial development. Especially for private non-financial enterprises, in the difficult situation of industrial development, in order to cope with the challenges of rising business costs, shrinking profit margins, and low investment returns, they have massively bypassed the traditional financial regulatory system and engaged in shadow banking business (Huang Xianhuan et al., 2021), resulting in the increasingly prominent phenomenon of shadow bankingization of private non-financial enterprises today.

Then, can the construction of big data inhibit the shadow bankingization of private non-financial enterprises? Although there is no direct evidence to support this conclusion, some relevant indirect evidence can still be found through existing literature for inference. On one hand, in previous studies on the construction of big data, Li Hui (2019) proposed that the construction of big data promotes the integration of big data and the real economy, and drives the high-quality development of the real economy; Cao Yuhao (2024) found that the construction of big data can accelerate the transformation and upgrading of the real industry, ensuring the healthy development of the real industry itself, thereby reversing the situation of economic "de-industrialization and towards virtualization"; Du Zhiqian and Zhao Chunyan (2024) pointed out that the construction of big data plays a significant role in governing the financialization of enterprises, and can effectively curb the trend of non-financial enterprises "de-industrialization". All the above research on the construction of big data indicate that the construction of big data can promote the development of the real economy of enterprises and inhibit the phenomenon of enterprises "de-industrialization". On the other hand, in previous studies on shadow banking, Fei Jiaqi (2024) found that as the level of digital finance development increases, the investment activities of non-financial enterprises in shadow banking business will be restricted; Wang Yao and Huang Xianhuan (2024) indicated that when non-financial enterprises have high profitability in their main businesses, digital finance development can effectively curb shadow bankingization; furthermore, Zeng Shuheheng (2024) pointed out that big data tax collection and management can also significantly inhibit shadow bankingization of physical enterprises. The above research on enterprise shadow banking indicates that digital construction has a significant inhibitory effect on enterprise shadow bankingization.

Based on the above analysis, we infer that the construction of big data can curb the shadow banking activities of private non-financial enterprises. Therefore, this paper puts forward the following hypothesis:

H1: Big data modeling can significantly curb the shadow banking phenomenon of private non-financial enterprises.

2.2.2 The Internal Mechanism by Which Big Data Construction Affects the Shadow Banking Transformation of Private Non-financial Enterprises

(1) The Mediating Role of Information Asymmetry

On the one hand, increasing the transparency of enterprise information and reducing information asymmetry can effectively curb the shadow bankingization of non-financial enterprises (Huang Xianhuan and Yao Rongrong, 2021). Existing studies have found that a significant increase in information transparency, an effective reduction in information asymmetry, and the intensification of market competition are significantly positively correlated (Du Zhiqian & Zhao Chunyan, 2024). In a fierce competition, enterprises need to depend on a complete and precise information exchange system to keep their competitive advantages. This system not only assists enterprises in correctly understanding the development trends of the industry but also enables them to thoroughly know the strategic plans of competitors and variations in market requirements. When enterprises actively decrease the information asymmetry and share more information with other market participants, not only will the fairness of the market be improved, but enterprises can also react more quickly to the market changes and enhance their competitiveness (Du Zhiqian & Zhao Chunyan, 2024). As a result, the incentive for arbitrage will be restrained (Sun Zheyuan, 2022), the unnecessary short-term behaviors, such as financial investments, will be reduced (Jan et al., 2017) and finally, the shadow banking of enterprises will be suppressed.

On the other hand, the construction of big data is an important way to increase the transparency of enterprise information and reduce information asymmetry (Zhang Mingdu et al., 2024). Firstly, by leveraging standardized, transparent, and informationized data transaction processes and digital sharing mechanisms, enterprises can easily and efficiently obtain the required data, thereby significantly reducing the difficulty and complexity of information acquisition, and greatly increasing the transparency of enterprise information; Secondly, the construction of big data can help enterprises improve data collection, storage, and processing work, with efficient data support, assisting enterprises in fully understanding market trends and industry dynamics, and effectively reducing the degree of information asymmetry.

Based on the above analysis, we believe that information asymmetry plays a mediating role between big data construction and the shadow bankingization of private non-financial enterprises. Therefore, the following hypothesis is proposed:

H2a: The construction of big data can curb the shadow banking activities of private non-financial enterprises by improving information asymmetry.

(2) The Mediating Role of Social Trust Level

Previous studies have shown that an increase in social trust can restrain the shadow banking behavior of non-financial enterprises (Huang Xianhuan & Yao Rongrong, 2021; Han Xun & Feng Yue, 2023). On one hand, compared with enterprises with low social trust, enterprises with higher social trust have more stable investor sentiments and are less sensitive to the short-term performance of the enterprise. This favorable social trust atmosphere helps to form more rational judgments and a long-term perspective among investors, reducing the short-sighted behavior of enterprises engaging in shadow banking due to the profit motive (Huang Xianhuan & Yao Rongrong, 2021), thereby inhibiting the level of shadow banking of enterprises. On the other hand, it is proposed that as the level of social trust increases, the external supervision and governance effect will be strengthened accordingly. The management behavior will be more constrained and restricted by the external reputation punishment mechanism, and thus will not rashly choose high-risk and high-cost shadow banking business that is outside the regulatory framework (Han Xun & Feng Yue, 2023). At the same time, with the intensification of the risk contagion effect, the willingness of enterprises to engage in shadow banking business has greatly decreased, thereby inhibiting the expansion of the shadow banking phenomenon.

At the same time, the construction of big data can enhance social trust and inject vitality into the information communication and transmission of business transactions (Zhang Mingduo & Li Xuesi, 2024), as well as improve the transparency of enterprise information. Within the framework proposed by Coleman for rational game theory, the acquisition of information is the core element guiding rational actors to formulate action strategies. Whether one can effectively grasp relevant information is directly related to whether social trust can be established and maintained (Wang Yishen, 2020). The construction of big data enhances the transparency of enterprise information, which precisely facilitates the establishment of social trust. On one hand, the construction of big data makes the sources of enterprises' credit data more diversified and multi-dimensional, reflecting the credit status of enterprise information subjects more truly and transparently, adding new impetus to the construction of credit systems in our country, and achieving true sharing of enterprise credit information resources (Jia Nan & Liu Guoshun, 2017), thereby providing a feasible path for reducing enterprise credit risks, eliminating the risk of enterprise default from the root, and facilitating the construction of regional credit platforms (Liu Xujie, 2024), and further promoting the formation and development of social trust. On the other hand, big data empowers the construction of a collaborative, participatory and shared governance system, enabling multiple social entities to jointly participate in governance (Liu Luning & He Weitao, 2023), significantly improving the effectiveness of governance, and in turn promoting the expansion of cooperative order and the reconstruction of social trust (Chen Hua & Ding Hong, 2014); at the same time, the practice of cooperative governance also enables the continuous generation, transmission, operation and strengthening of trust capital (Zhao Youhua, 2019), injecting inexhaustible impetus into the development of social trust.

From this, we believe that the level of social trust plays a mediating role in the relationship between big data construction and the shadow banking of private non-financial enterprises. To sum up, the following hypotheses are proposed:

H2b: The construction of big data can help reduce the shadow banking activities of private non-financial enterprises by enhancing social trust.

3. Research Design

3.1 Sample Selection and Data Sources

This paper selects private non-financial enterprises in prefecture-level cities of China as the original sample from 2012 to 2022. Based on the quasi-natural experiment of the national-level big data comprehensive experimental zone, the PSM-DID method is used to explore the impact of big data construction on the shadow bankingization of private non-financial enterprises. The data used in this study comes from the database of the School of Economics and Management. The initial sample data obtained is processed as follows: (1) Remove the financial industry samples; (2) Remove the real estate industry samples; (3) Remove the ST-class samples. After the above screening, a total of 29,641 sample observations were obtained. After PSM matching and excluding unmatched samples, a total of 11,517 sample observations were obtained. At the same time, the relevant continuous variables are processed with Winsorization within the range of 1% above and below, in order to reduce the influence of outliers on the sample results, and State and Excel are used to process the final sample data and conduct empirical analysis.

3.2 Variable Definition

3.2.1 Dependent Variable: Shadow Banking of Private Non-financial Enterprises

At present, there is no unified standard for measuring the scale of shadow banking in private non-financial enterprises. This paper, drawing on the measurement methods of Li Jianjun and Han Xun (2019) and Huang Xianhuan and Wang Cui (2021), divides the business mechanisms of enterprises engaging in shadow banking into two models: "substantive credit intermediation" and "shadow credit chain". "Substantive credit intermediation" is mainly measured by entrusted loans, entrusted wealth management, and private lending. "Shadow credit chain" is measured by calculating the financial products owned by enterprises such as bank wealth management, securities company wealth management, trust products, and structured deposits. Specifically: entrusted loans are the sum of other current assets in the financial statements, other non-current assets due within one year, and other non-current assets; the data of entrusted wealth management is obtained through the Guotai An database; due to the strong concealment of private lending, this paper also follows the research of Jiang et al. (2010), using the "other receivables" item in the balance sheet as a representation; the other current assets in the financial statement notes are used to measure the investment activities of enterprises participating in the shadow credit chain. Therefore, this paper ultimately measures the scale of shadow banking in private non-financial enterprises by adding the proportions of these two types of businesses to the total assets.

3.2.2 Explanatory Variable: Big Data Construction

This paper takes the "big data construction variable" (Bdc) as the core explanatory variable. Bdc = treat × post is the dummy variable for big data construction. Treat = 1 indicates that the enterprise is located in the approved area of the national-level big data comprehensive experimental zone, while treat = 0 indicates that the enterprise's location is outside the experimental zone. Post = 1 indicates that it is after the establishment of the national-level big data comprehensive experimental zone, while post = 0 indicates that it is before the establishment of the experimental zone.

3.2.3 Mediating Variable

(1) Information Asymmetry

Information asymmetry: It is defined as the situation in market transactions where the supply and demand sides of a product do not have symmetrical information about the product's quality, performance, etc. This easily leads to conflicts of interest between the parties involved in the transaction, affects the principles of fairness and justice in society, and makes it difficult to achieve high-efficiency market resource allocation. In summary, it has a considerable impact on social and economic development. In this paper, the measurement method of this variable refers to Zhang Yan and Zhou Yanqiu (2013), Zhou Kaiguo et al. (2014), and Liu Liya et al. (2019), using information asymmetry (Ic) as a proxy variable for information optimization. Since information asymmetry is often used to measure market efficiency and the degree of inequality among market participants, it is determined to have a negative correlation with information optimization.

(2) The Level of Social Trust

Degree of social trust: It is a comprehensive evaluation index that measures the credit status exhibited by an organization in social activities, reflecting the credit behaviors and integrity level of enterprises in economic activities, contract performance, ethics, and morality. This concept not only focuses on safety and efficiency issues in economic transactions but also maintains the normal order of economic activities and social life, promoting healthy economic and social development. This paper draws on the research methods of Han Xun and Feng Yue (2023) to measure intermediary factors, using shareholding concentration (Top1) as a proxy indicator to analyze the degree of social trust via the three-step measurement method. The analysis indicates that this factor affects the shadow banking behavior of non-financial enterprises through the reputation penalty cost of managerial opportunistic behavior, the risk of managers' hidden negative information being discovered, collateral requirements of financial intermediaries, and the default risk of borrowing enterprises.

3.2.4 Selection of Control Variables

In the regression model, based on existing research, this paper selects other indicators that may affect the shadow banking of private non-financial enterprises as control variables, including: debt-to-asset ratio, equity concentration, asset turnover, concentration of shareholding structure, inventory turnover, enterprise size, and revenue growth rate. The specific definitions of the variables are shown in Table 1.

Table 1. Definition and Explanation of Variables

Variable Type	Variable Name	Variable Symbol	Variable Description
Dependent Variable	Shadow banking of private non-financial enterprises	Sbank	(Entrusted loans, entrusted wealth management, private lending, quasi-financial products) / total assets
Explanatory Variable	Big Data Construction	Bdc	Policy dummy variable for the construction of national-level big data experimental zones
Control Variable	Debt-to-asset Ratio	Lev	Total Liabilities / Total Assets
	Equity Concentration	Top1	Number of shares held by the largest shareholder / Total number of shares
	Asset Turnover	ATO	Net main business income / Average total assets
	Equity Structure Concentration	Top10	Shareholding ratio of the top ten shareholders
	Inventory Turnover	INV	Cost of main business / Average inventory balance
	Enterprise Scale	Size	Measured by asset size, operating revenue, and other aspects
	Revenue Growth Rate	Growth	Increase in operating revenue / total operating revenue of the previous year
Mediator variable	Information Asymmetry	Ic	The evaluation results of the company’s annual report in terms of timeliness, accuracy, completeness, and legality of information disclosure
	Level of Social Trust	Dst	China Urban Commercial Credit Environment Index compiled by the China Academy of Management Science

3.3 Baseline Model Setting

This article refers to previous studies, constructs a multi-period DID regression model for empirical testing, and explores the impact of big data development on the shadow banking of private non-financial enterprises:

$$\mathrm{Sbank}_{kt}=\alpha_0+\alpha_1\mathrm{Bdc}_{kt}+\alpha_2\mathrm{Control}_{kt}+\mu_i+\mu_t+\varepsilon_{kt} \quad (1)$$

Among them: Sbank is the scale of shadow banking of private non-financial enterprises; Bdc = treat × post represents big data construction; Control is the set of control variables; $\mu_i \& \mu_t$ are dual fixed effects of enterprise individual and time; ε_{kt} is the error term.

3.4 Descriptive Statistical Analysis of Variables

This article takes private non-financial enterprises in 300 prefecture-level and above cities from 2012 to 2022 as the research object, analyzing the impact effect of big data construction on the shadow banking of private non-financial enterprises, with a total of 29,641 observations.

Table 2. Descriptive Statistics

Variable Type	Variable Name	Variable Symbol	Observation	Mean	Standard deviation	Minimum	Maximum
Dependent Variable	Shadow banking of private non-financial enterprises	Sbank	29641	0.139	0.242	0.000	1.447
Explanatory Variable	Big Data Construction	Bdc	29641	0.340	0.474	0.000	1.000
Control Variable	Debt-to-asset Ratio	Lev	29641	0.338	0.148	0.080	0.754
	Equity Concentration	Top1	29641	0.650	0.434	0.072	3.151
	Asset Turnover	ATO	29369	0.124	0.102	0.000	0.931
	Equity Structure Concentration	Top10	29641	0.407	0.206	0.008	1.957
	Inventory Turnover	INV	29641	0.589	0.154	0.013	1.012
	Enterprise Scale	Size	29641	22.179	1.314	15.577	28.636
	Revenue Growth Rate	Growth	29632	0.000	0.001	-0.000	0.135

Table 2 lists the descriptive statistical analysis results of the variables. In terms of the shadow banking (Sbank) indicator for private non-financial enterprises, the mean is 0.139 and the standard deviation is

0.242, indicating that the average shadow banking proportion of private non-financial enterprises is 13.9%, and there is some variation in the degree of shadow banking among different private non-financial enterprises. The big data construction (Bdc) indicator shows a mean of 0.340 and a standard deviation of 0.474, suggesting that 34.0% of the samples have engaged in big data construction, and there is considerable variation in big data construction among private non-financial enterprises.

4. Analysis of Empirical Results

4.1 Analysis of Baseline Regression Results

This paper conducts a verification analysis on the role of big data construction in curbing the shadow banking phenomenon of private non-financial enterprises. Through empirical testing using the difference-in-differences method, the regression results are shown in Table 3. The results indicate that big data construction plays a significant role in curbing the shadow banking phenomenon of private non-financial enterprises.

Column (1) only includes the control variables to improve the accuracy of the model. This indicates that regardless of whether other variables' influences are considered, the construction of big data operates at a highly significant level and has a positive governance effect on the shadow banking of private non-financial enterprises. Further, in Column (2), both independent variables and control variables are considered. The result shows that the regression coefficient of Bdc is -0.015, with a t-value of -2.317, which passes the 5% significance test, indicating that the construction of big data can effectively suppress the shadow banking of private non-financial enterprises. Therefore, H1 is verified.

Table 3. Baseline Regression: Big Data Construction and Shadow Banking of Private Non-Financial Enterprises

Variable	(1) Sbank	(2) Sbank
Bdc		-0.015**
		(-2.317)
Top1	0.048*	0.047*
	(1.771)	(1.730)
ATO	-0.025***	-0.026***
	(-3.633)	(-3.700)
INV	-0.124***	-0.123***
	(-4.806)	(-4.736)
Lev	-0.176***	-0.176***
	(-11.572)	(-11.570)
Top10	-0.121***	-0.123***
	(-5.357)	(-5.430)

Size	-0.010**	-0.010**
	(-2.532)	(-2.499)
Growth	0.580***	0.616***
	(16.722)	(15.497)
constant term	0.452***	0.451***
	(5.350)	(5.342)
observed value	29360	29360
Adjusted R-squared	0.049	0.049
Individual fixed effect	YES	YES
Fixed effect of year	YES	YES

Note. The values in parentheses are the robust t-values. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively, and the same applies below.

4.2 Robustness Checks

This section conducts necessary robustness checks on the research results, including three steps: the PSM-DID test, the exclusion of extreme value samples, and the counterfactual test.

4.2.1 PSM-DID Analysis

Drawing on the approach of Zhang Mingdou and Li Xuesi (2024), to account for the estimation errors in policy effect evaluation caused by sample selection bias, when selecting the control group, it is necessary to identify individuals or groups that are as similar as possible to the treatment group in terms of observable characteristics, thereby reducing the potential differences between the two groups. To achieve this goal, using the Propensity Score Matching (PSM) method for sample matching is an effective approach. The regression results of the PSM-DID model are shown in Table 4.

Table 4. PSM-DID Test

Variable	Sbank
Bdc	-0.018**
	(-2.153)
Control Variables	YES
Observations	11517
Adjusted R-squared	0.056
Individual Fixed Effects	YES
Year Fixed Effects	YES

The results show that the coefficient of Bdc is -0.018, which is significantly negative at the 5% significance level. Other control variables also have significant effects on Sbank. The adjusted R-squared is 0.056. Meanwhile, individual fixed effects (μ_i) and year fixed effects (μ_t) are controlled, further verifying the robustness of the baseline regression results.

Although the difference-in-differences method isolates the average treatment effect of big data construction, the pilot zone construction does not fully meet the strict criteria of a natural experiment. Therefore, sample selection bias may still exist, potentially leading to endogeneity problems. To address this issue, this paper conducts a robustness check using the caliper matching method based on the Propensity Score Matching (PSM) and Difference-in-Differences (DID) model.

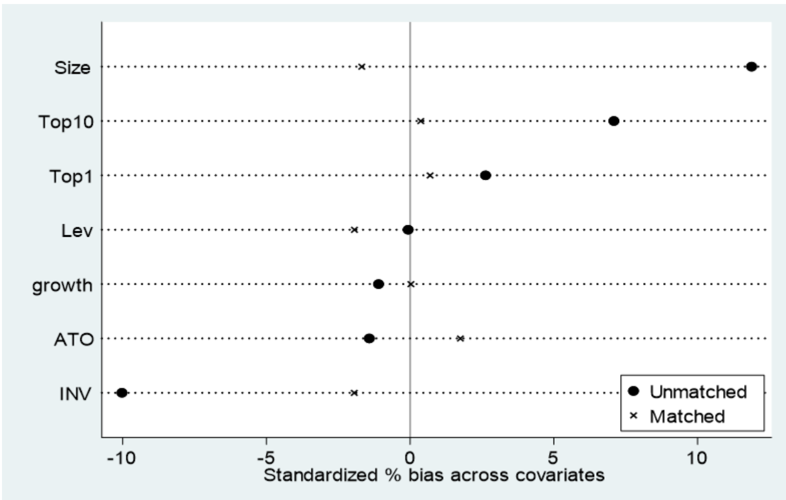

Figure 1. Matching Effect Plot

Figure 1 presents the balance test results of the propensity scores. Except for Lev and ATO, the standardized biases of the remaining variables are reduced after matching.

4.2.2 Exclusion of Extreme Samples

Drawing on the approach of Du Zhiqian, Zhao Chunyan, et al. (2024), compared with ordinary prefecture-level cities, China's municipalities, provincial capitals, and sub-provincial cities have more prominent advantages in resource endowments and market environments. To eliminate the potential interference of extreme values on the empirical regression results, when conducting the DID identification analysis, samples of private non-financial firms located in these municipalities, provincial capitals, and sub-provincial cities are excluded. The test results are shown in Table 5.

Table 5. Test After Excluding Extreme Samples

Variable	Sbank
Bdc	-0.024***
	(-3.113)
Control Variables	YES
Observations	23165
Adjusted R-squared	0.053
Individual Fixed Effects	YES
Year Fixed Effects	YES

The results show that the coefficient of Bdc is -0.024***, which is significantly negative at the 1% level. The coefficients and significance levels of other variables are generally consistent with those before excluding the municipality samples. This indicates that the research conclusions remain robust after excluding the municipality samples, further supporting the finding that big data construction inhibits the shadow banking of private non-financial firms.

4.2.3 Counterfactual Test

To verify the reliability of the conclusions, this paper adopts the counterfactual test following the approach of Zhang Mingdou, Li Xuesi, et al. (2024). Specifically, the approval time for the big data comprehensive pilot zones is artificially moved forward, assuming that the approval occurred in 2013 and 2014, respectively. As shown in Table 6, the coefficients of Bdc_2013 and Bdc_2014 are both insignificant, which aligns with expectations. The coefficients and significance levels of other variables are similar to those in previous results, further demonstrating the robustness of the research conclusions. Taken together, this study exhibits certain robustness across different samples and counterfactual tests. After excluding the municipality samples, the results remain significant, and the adjusted R-squared improves, indicating a certain degree of model stability. The insignificance of Bdc in the counterfactual test also meets expectations, further validating the reliability of the model.

Table 6. Counterfactual Test

Variable	（1）Sbank	（2）Sbank
Bdc_2013	-0.008	
	(-0.925)	
Bdc_2014		-0.012
		(-1.459)
Control Variables	YES	YES
Observations	23165	23165
Adjusted R-squared	0.053	0.053

Individual Fixed Effects	YES	YES
Year Fixed Effects	YES	YES

5. Further Analysis

5.1 Mechanism Testing

The previous findings show that big data construction can inhibit the shadow banking of private non-financial firms. Then, through which channels does big data construction affect the shadow banking of private non-financial firms? In light of this, this section constructs the following mediation effect model, in which big data affects the shadow banking of private non-financial firms by influencing corporate information asymmetry (Ic) and the level of social trust (Dst)：

$$\mathrm{Mediator}_{kt}=\beta_0+\beta_1\mathrm{Bdc}_{it}+\beta_2\mathrm{Control}_{kt}+\mu_i+\mu_t+\rho_{kt} \quad (2)$$

$$\mathrm{Sbank}_{kt}=\gamma_0+\gamma_1\mathrm{Mediator}_{it}+\gamma_2\mathrm{Bdc}_{it}+\gamma_3\mathrm{Control}_{kt}+\mu_i+\mu_t+\sigma_{kt} \quad (3)$$

In this model, Sbank, Bdc, and Control have the same meanings as in Equation (1). Mediator represents the mechanism variables, including corporate information asymmetry (Ic) and the level of social trust (Dst). β and γ are constant terms, and ρ_{kt} and σ_{kt} are error terms.

5.1.1 Testing of the Information Asymmetry Mechanism

Take a look at Table 7. In Column (1), the coefficient is -0.014 and significant at the 5% level. That tells us big data construction really does help cut back on shadow banking among private non-financial firms. Now Column (2) — the coefficient is -0.033, also significant at 5%. So big data construction also eases information asymmetry.

Then Column (3): the coefficient for Ic is -0.009, significant at 1%. That means reducing information asymmetry can effectively keep shadow banking in check.

Put these together. How does big data construction work its magic? By using its tech advantages — data integration and analysis — it narrows the information gap between firms and outsiders. That leads to better corporate disclosure, more ways to gather information, and greater transparency. So here’s the bottom line: big data construction curbs shadow banking in private non-financial firms by lowering information asymmetry. When corporate information becomes more transparent and easier to access, firms are less likely to jump blindly into financial activities. That’s why H2a is supported.

Table 7. Information Asymmetry Mechanism

Variable	（1）Sbank	（2）Ic	（3）Sbank
Bdc	-0.014**	-0.033**	-0.014**
	(-2.138)	(-2.009)	(-2.181)
Ic			-0.009***
			(-2.598)
Constant	0.549***	6.291***	0.606***

	(6.247)	(23.610)	(6.686)
Control Variables	YES	YES	YES
Observations	28582	28582	28582
Adjusted R-squared	0.491	0.632	0.491
Individual Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES

5.1.2 Testing of the Social Trust Mechanism

Look at Table 8. Column (1) gives a coefficient of -0.017, significant at the 5% level. That tells us big data construction really does put a damper on shadow banking in private non-financial firms.

Now check Column (2). The coefficient is 0.026, significant at 1%. So big data construction also boosts social trust by quite a bit.

Then Column (3). The coefficient for Dst is -0.144, significant at 5%. That means when social trust goes up, shadow banking tends to go down — at least to some extent.

Why does that matter? High social trust helps make information more transparent, and it nudges financial institutions to build proper digital financial service systems. These numbers line up nicely with what the mediation test predicted. In other words, big data construction gives us a kind of trust index, and that trust plays a key role in how big data affects shadow banking. So H2b holds up.

Table 8. Social Trust Mechanism Test

Variable	(1)Sbank	(2)Dst	(3)Sbank
Bdc	-0.017**	0.026***	-0.013*
	(-2.485)	(21.589)	(-1.823)
Dst			-0.144**
			(-2.028)
Constant	0.538***	4.291***	1.155***
	(5.545)	(262.625)	(3.695)
Control Variables	YES	YES	YES
Observations	24632	24632	24632
Adjusted R-squared	0.494	0.925	0.494
Individual Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES

5.2 Heterogeneity Test

5.2.1 Heterogeneity in Regional Economic Development Levels

China's eastern region and its central/western regions are pretty different when it comes to economic development. The east is more developed and has plenty of financial resources, so companies there have lots of ways to raise funds. Out west and in the middle, though, firms still lean heavily on traditional options — bank loans being a big one. By looking at how corporate financialization varies across these regions, we can see whether the big data pilot zone policy works differently depending on where you are. That helps us come up with better, more tailored policy advice — ones that actually fit each region's unique situation.

Table 9. Test on Regional Economic Development Levels

	（1）Eastern Region	（2）Central Region	（3）Western Region
Variable	Sbank	Sbank	Sbank
Bdc	-0.014*	-0.024	-0.034
	(-1.758)	(-1.519)	(-1.478)
Constant	0.549***	0.313**	0.185
	(5.076)	(2.362)	(1.008)
Control Variables	YES	YES	YES
Observations	20916	5007	3240
Adjusted R-squared	0.057	0.040	0.064
Individual Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES

Looking at Table 9, big data construction doesn't seem to do much for firms in the central and western regions — the coefficients are -0.024 and -0.034, respectively. But in the eastern region, it's a different story. The coefficient there is -0.014, significant at the 10% level. So big data construction does help rein in shadow banking among private non-financial firms in the east.

Why the difference? There are a couple of reasons. First, how well government policies get implemented varies a lot across regions. Eastern governments are pretty good at putting policies into action, so you can actually see the effects. The central and western regions, on the other hand, often run into implementation problems, which makes the governance impact weaker. So the gap in government execution capacity is probably a big factor behind this regional difference. Second, the eastern region has a more advanced and better-organized industrial system. Big data construction there may be more targeted at curbing corporate shadow banking, which is why the effect stands out. Meanwhile, the central and western regions still rely heavily on traditional manufacturing, and policy guidance isn’t as strong — so the governance results just aren’t as good.

5.2.2 Heterogeneity in Corporate Technological Attributes

High-tech firms and non-high-tech firms face different financial challenges and needs. Analyzing this issue helps to better understand whether big data construction initiatives can meet the financialization governance needs of different industries, provides practical guidance for policy formulation, and facilitates the satisfaction of diverse governance needs while promoting the sustainable development of various industries.

Table 10. Corporate Technological Attributes Test

	(1)High-tech Firms	(2)Non-high-tech Firms
Variable	Sbank	Sbank
Bdc	-0.018*	-0.011
	(-1.840)	(-1.284)
Constant	0.585***	0.412***
	(4.483)	(3.229)
Control Variables	YES	YES
Observations	14086	13144
Adjusted R-squared	0.069	0.045
Individual Fixed Effects	YES	YES
Year Fixed Effects	YES	YES

If you look at Table 10, the big data pilot zone policy has a stronger effect on high-tech firms than on non-high-tech ones. For high-tech firms, the Bdc coefficient comes in at -0.018 and is significant at the 10% level. For non-high-tech firms, it’s only -0.011. So the policy works better at keeping shadow banking in check among high-tech companies.

What explains this gap? Well, by upgrading digital infrastructure, the policy creates a better environment for high-tech firms to operate in. It sharpens their information processing, reduces uncertainty in the business environment, and lowers the risks tied to information asymmetry. Non-high-tech firms, on the other hand, probably don’t use big data tools as heavily or as effectively. So the benefits they get end up being smaller compared to what high-tech firms enjoy.

6. Research Findings and Implications

6.1 Research Findings

Based on the data of private non-financial enterprises which conduct business in prefecture-level cities participating in the national big data comprehensive pilot zone, from 2012 to 2022, the research uses a

PSM-DID model to empirically investigate the impact of big data construction on shadow banking activities in these enterprises and the possible mechanisms. The findings are as follows: firstly, big data construction can reduce shadow banking in private non-financial enterprises and this conclusion is still valid after removing some special samples and performing counterfactual and PSM tests. Secondly, decreased information asymmetry and enhanced social trust are the main mechanisms by which big data construction controls such shadow banking behaviors. Furthermore, the inhibiting effect of big data construction on shadow banking is more significant in the eastern region, where the economic development is higher, than in the central and western regions. Additionally, the influence is more evident for private non-financial enterprises in high-tech industries than those in non-high-tech industries.

6.2 Research Implications

The results of this research have important practical significance for both the national government and private non-financial enterprises. By making full use of their own advantages and duties, the government and enterprises can cooperate to advance big data development, thus efficiently preventing shadow banking. The detailed implications are as follows.

6.2.1 At the Government Level

To begin with, the government ought to keep developing the national big data comprehensive pilot zone policy, enhance the supporting regulatory environment, and take an active role in promoting the construction of big data. Since the impact of big data construction on shadow banking is different in various regions, the government needs to use different regional policies depending on how economically advanced the regions are and what their technological innovation capabilities are. The priority in less developed areas must be on developing big data infrastructure; in more developed areas, it can be on the use and further development of big data technology. Thirdly, the government needs to enhance the regulation of big data usage to guarantee the accuracy, integrity, and security of data. It should help enterprises and financial institutions develop their data analytics, employing big data technologies to decrease information asymmetry and boost market transparency thus minimizing the utilization of shadow banks. Besides, the government may encourage the development and adoption of corporate social trust frameworks, which will assist enterprises to become more transparent and credible, which in turn will contribute to the sound growth of financial markets.

6.2.2 At the Enterprise Level

To ensure that any given private non-financial corporation has strong corporate performance and an excellent reputation, it is important to react to government policies positively by building more robust big data, alleviating information asymmetry, and fostering social trust. Several actions might be taken. Firstly, the private non-financial enterprises are required to take an active approach to big data technologies to minimize information asymmetry, enhance decision-making, and diminish reliance on shadow banking. Secondly, they must address their social responsibilities and engage actively in the social responsibility programs, which will boost their sense of social trust and public credibility, and will also help to create more confidence in the company in the market and decrease the chances of shadow banking operations. Thirdly, companies need to develop region-specific approaches that are adapted to the level of economic development of various regions. One example is how they can obtain assistance and resources of the local government in order to promote the use of big data in less developed areas. Fourth, private non-financial enterprises need to make investments into big data and technological innovation (particularly in high-tech industries) strategically and use high-tech tools to streamline business processes and financing models.

7. Limitations of the Study and Future Prospects

This paper examines how big data construction has influenced the activities of shadow banking of non-financial private enterprises. The present data sample is however restricted to only those enterprises that operate in prefecture-level cities that form part of the national big data comprehensive pilot zone during the time interval between 2012 and 2022, and the size as well as the quality of the sample may be considered slightly restricted. Further research can add to the information with additional collection of secondary sources and questionnaire surveys. Moreover, information asymmetry and social trust are the only two factors that have been explored as mediating mechanisms in this study. Other potential pathways, including resource allocation and total factor productivity, could be examined and confirmed in future work, thus clarifying further the effect of big data construction on shadow banking. Lastly, the research subject of this study is the private enterprises of the non-financial sector and does not compare with non-private enterprises. Further studies could conduct a comparative analysis of private and non-private non-financial enterprises and identify at a more profound level the peculiarities of shadow banking in private non-financial companies and the role that big data construction plays in them to offer more realistic and practical policy suggestions.

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