Risk and Financial Management; Vol. 6, No. 2; 2025
ISSN 2690-9790 E-ISSN 2690-9804
https://doi.org/10.30560/rfm.v6n2p8

The Role of Big Data Finance in Supporting and Supervising Corporate Financial Decision-Making

Chenying Xiong[1]

[1] Tianjin University of Commerce, Tianjin, China

Correspondence: Chenying Xiong, Tianjin University of Commerce, Tianjin 300134, China

Received: June 11, 2025 Accepted: July 19, 2025 Online Published: July 22, 2025

Abstract

With the rapid adoption of big data technologies in finance, opportunities have emerged to enhance the transparency and compliance of corporate financial decision-making. This paper first reviews the concept and evolution of big data finance, then constructs a "supportive supervision–decision optimization–risk prevention" theoretical framework. Using panel data from representative listed firms, we select key variables and employ multivariate regression and robustness checks to empirically assess the supervisory effects of big data finance in the decision-making process. Our findings show that big data finance significantly strengthens firms' real-time internal control monitoring capabilities, improves the accuracy of financial budgeting and forecasting, and enhances the quality of financial reporting. Moreover, its supervisory function has a pronounced positive impact on reducing financial fraud risk and boosting corporate performance. Finally, we offer management recommendations—such as improving big data platform infrastructure, reinforcing data governance and privacy protection, and fostering coordinated mechanisms between regulators and market participants—to provide practical guidance for more scientific financial decision-making and a more effective regulatory system.

Keywords: big data finance, financial decision-making, supportive supervision, internal control, risk prevention

1. Introduction

In recent years, a new wave of financial transformation centered on big data technologies has profoundly reshaped corporate financial management and decision-making. Massive, multi-source, real-time data streams not only offer unprecedented insights but also demand greater transparency and compliance in traditional decision processes. In an increasingly competitive capital market, relying on experience and limited financial statements no longer suffices to meet the dual goals of risk control and value creation. At the same time, regulators and stakeholders impose ever-stricter expectations on the accuracy and timeliness of corporate disclosures, compelling firms to leverage big data finance to reinforce internal controls, optimize budget forecasts, and build dynamic, traceable decision loops.Against this backdrop, we adopt a "supportive supervision–decision optimization–risk prevention" theoretical framework and design an empirical model using panel data from representative listed companies. Based on a literature review, we propose two core hypotheses: first, that big data finance enhances firms' real-time internal control monitoring capacity; second, that it significantly improves financial reporting quality and reduces fraud risk. Through descriptive statistics, regression analysis, and various robustness tests, we systematically evaluate the supportive supervision effects of big data finance across key decision-making stages—including budgeting, performance evaluation, and risk warning. Our results enrich the theoretical dialogue at the intersection of big data and financial decision-making and offer actionable management insights for platform development, data governance, and regulatory coordination.

2. Literature Review

2.1 Concept and Development of Big Data Finance

Big data finance refers to the systematic practice of fully utilizing vast, multi-source, real-time data in the financial sector—combined with advanced data mining, machine learning, and artificial intelligence—to conduct in-depth analyses and forecasts of customer behavior, market dynamics, and risk profiles. Unlike traditional financial analysis methods that rely primarily on historical financial statements and limited market surveys, big data finance emphasizes a "data-driven, integrated, real-time" approach. By merging structured transaction data, semi-structured log data, and unstructured text and image data, it enables dynamic monitoring and fine-grained management across the entire financial process. Its core value lies in significantly improving the accuracy of credit assessment, fraud detection, and asset pricing through large-scale data modeling, while real-time processing capabilities allow firms to receive timely alerts and adjust strategies swiftly when market fluctuations or anomalies arise[1].

The evolution of big data finance can be divided into three stages:Technology Exploration (circa 2010): Financial institutions experimented with big data platforms (e.g., Hadoop, NoSQL) to handle structured data, enhancing transaction throughput and storage capacity.Business Integration (2013–2018): With the maturation of machine learning and real-time streaming technologies (e.g., Spark Streaming, Flink), institutions began integrating big data with risk control, marketing, and customer relationship management, implementing applications such as credit risk pricing, precision marketing, and customer profiling.Ecosystem Construction (2019–present): Big data finance has moved toward an open ecosystem. Traditional banks and insurers have strengthened internal data platforms, while internet giants and fintech firms have launched open platforms—via APIs and data alliances—extending big data capabilities to SMEs and individuals. This has accelerated the emergence of supply-chain finance, blockchain-based risk control, and robo-advisory services. As data governance, privacy protection, and regulatory compliance have become more stringent, big data finance is steadily evolving toward standardized, sustainable practices that provide robust technical and institutional support for corporate financial decision-making[2].

2.2 Corporate Financial Decision-Making and Supervisory Mechanisms

Corporate financial decisions—such as capital structure, investment project selection, and budgeting—aim to maximize value under controlled risk. Early research focused on decision models like net present value (NPV), internal rate of return (IRR), and the capital asset pricing model (CAPM). However, as market complexity and information asymmetry increased, models relying solely on financial data proved limited. Scholars began emphasizing supervisory and constraint mechanisms within decision processes. From the agency theory perspective, enhancing board independence and audit committee functions reduces managerial risk-taking[3]. Behavioral finance highlights how transparent disclosure and stakeholder involvement can correct decision biases. Overall, the literature agrees that integrating decision models with effective supervision is essential for improving decision quality.Supervisory mechanisms encompass internal controls and external regulation. Internal controls focus on process design and risk warnings, following frameworks such as COSO's five components: control environment, risk assessment, control activities, information and communication, and monitoring—forming a top-down supervision loop. Empirical studies demonstrate that robust internal controls lower decision errors and play a vital role in budget compilation and execution. Externally, securities regulators, audit firms, and credit rating agencies impose constraints on financial report authenticity through compliance checks, independent audits, and ratings. Recently, scholars have explored the role of regulatory technology (RegTech) in strengthening external oversight and enhancing audit efficiency, offering new perspectives on compliance and transparency in financial decision-making[4].

3. Theoretical Framework and Research Hypotheses

3.1 Mechanism Model of Supportive Supervision

The supervisory mechanism of big data finance can be abstracted into a closed-loop model consisting of four interacting stages: data collection, intelligent analysis, risk warning, and decision feedback. First, at the data-collection stage, firms build a unified big-data platform to standardize and consolidate multi-source internal and external data—including transaction records, market quotes, media and news feeds, and social-network information—thereby laying a solid foundation for subsequent analysis[5]. Next, in the intelligent-analysis stage, machine-learning and real-time stream-processing technologies are applied to mine and model these data from multiple angles. This process both identifies abnormal budget variances and uses natural-language processing and text-mining techniques to detect potential inconsistencies in financial reports, yielding precise quantitative indicators for supervision. Third, at the risk-warning stage, the system generates real-time alerts—based on predefined thresholds and dynamic risk-scoring models—whenever internal-control failures, budget overruns, or fraudulent activities are likely to occur. It then pushes visualized reports or dashboard displays of risk levels, implicated business units, and suspicious transaction details to decision-makers and relevant oversight bodies. Finally, in the decision-feedback stage, management adjusts budget plans or execution strategies in response to these alerts, and integrates the feedback and new operational data into the next analysis cycle, thus achieving continuous, closed-loop supervision and optimization of the entire decision-making process.At its core, this model leverages big data technology to strengthen supervisory functions, transforming the traditional "post-audit" approach into a "real-time monitoring plus early warning" paradigm. By fusing multi-source data and performing real-time analysis, it enhances both the timeliness and accuracy of supervision while reducing decision biases caused by information lag or insufficient samples. Moreover, dynamic risk scores and interactive visual dashboards allow management to trace key decision points and anomalies clearly, enabling internal controls and external oversight to work in concert and providing robust supervisory support for financial decision-making. This mechanism model underpins the variable definitions and hypothesis tests in our subsequent empirical research[6].

3.2 Formulation of Research Hypotheses

Based on the above "data collection–intelligent analysis–risk warning–decision feedback" mechanism model, we propose two core hypotheses to evaluate the effectiveness of big data finance in providing supportive supervision during corporate financial decision-making[7].

Hypothesis 1: The greater the extent of a firm's big data finance platform adoption, the stronger its real-time internal-control monitoring capability.Continuous multi-source data collection and intelligent analysis enable big data finance to capture budget deviations, abnormal transactions, and process failures promptly, thereby significantly improving the timeliness and effectiveness of internal monitoring over financial activities.

Hypothesis 2: The more comprehensive the supervisory functions of big data finance, the higher the quality of financial reporting and the lower the risk of financial fraud.Supported by real-time alerts and visual feedback, management can more accurately identify potential inconsistencies or manipulations and incorporate risk-control measures into decision processes, thus enhancing the authenticity and completeness of financial disclosures and effectively suppressing fraud incidents[8].

4. Research Design and Methods

4.1 Data Sources, Sample Selection, and Variable Definitions

To ensure representativeness and robustness, our data are drawn from the Wind Info and CSMAR databases, covering A-share main-board and CSI 300 constituent firms in China from 2018 to 2023. We exclude "ST" firms with two consecutive years of financial irregularities or delisting warnings, as well as firms with incomplete financial statements or annual-report disclosures, yielding a balanced panel of approximately 1,200 companies. Industry classifications follow Wind's Level-1 categories. All financial figures are adjusted for price comparability within each year, and extreme values (top and bottom 1 percentiles) are winsorized[9].

We define the key variables as follows:Constructed on a 0–1 scale, this composite index normalizes the frequency of keywords such as "big data," "cloud computing," and "artificial intelligence" in annual reports, and incorporates indicators of whether the firm has established a dedicated big-data platform and disclosed investments in big-data projects. A higher BDI indicates deeper application of big data finance in supervisory functions.Measured by the negative logarithm of the average response time (in days) to internal-control deficiencies, as disclosed in annual internal-control test results. A larger value denotes more timely monitoring and response.FRQ is proxied by the negative absolute value of discretionary accruals (|DA|) from the modified Jones model, with higher values indicating better reporting quality. FRAUD is measured by the count of financial restatements or regulatory penalties over the past three years, with lower counts indicating lower fraud risk.Company size (log of total assets), profitability (ROA), leverage ratio, state-ownership dummy (SOE = 1 for state-owned enterprises), and independent-director ratio (Indep), as well as industry and year fixed effects, to mitigate omitted-variable bias.These variable choices capture both the multidimensional nature of big-data technology adoption and the quantitative assessment of supervisory outcomes, laying a solid foundation for our empirical models and tests[10].

4.2 Empirical Model Construction and Testing Methods

To examine the impact of big data finance adoption on internal-control monitoring, financial reporting quality, and fraud risk, we first employ panel fixed-effects regressions. The BDI serves as the core explanatory variable, while ICM, FRQ, and FRAUD are used respectively as dependent variables. We include the control variables listed above, along with company and year fixed effects, to account for industry heterogeneity and temporal trends. Robust standard errors correct for potential heteroskedasticity and serial correlation, ensuring reliable estimates.

To address endogeneity concerns and test robustness, we implement three additional checks:Instrumental-Variable Estimation: We use industry-level big-data infrastructure investment intensity as an instrument for BDI and apply two-stage least squares to correct for potential simultaneity.Subsample Analysis: We divide the sample by ownership type (state-owned vs. non-state-owned) and firm size (large/medium vs. small), conducting separate regressions to assess heterogeneity in the supervisory effects of big data finance.Alternative Measures: We replace ICM with the annual count of risk warnings and FRAUD with the frequency of major financial-misconduct incidents to verify that our main findings hold under different variable definitions.By triangulating evidence across multiple methods and measures, we aim to provide robust empirical support for the role of big data finance in enhancing supervisory effectiveness in corporate financial decision-making.

5. Empirical Analysis

5.1 Descriptive Statistics and Correlation Analysis

We first processed the balanced panel of 1,200 listed firms over 2018–2023 and computed descriptive statistics for our core and control variables, along with pairwise correlations (Table 1). The mean Big Data Finance Adoption Index (BDI) is 0.45, indicating a moderate level of big-data adoption in supervisory roles. The Real-Time Internal-Control Monitoring capability (ICM), after taking the negative log of average response days, has a mean of 2.10 and moderate dispersion. Financial Reporting Quality (FRQ) averages 0.72, reflecting generally high disclosure quality, while Fraud Risk (FRAUD) averages only 0.15 incidents over three years. Control variables—firm size (Size), return on assets (ROA), and leverage—also lie within expected ranges.

As the Table 1 shown, Correlation analysis shows BDI is significantly positively correlated with both ICM (0.42) and FRQ (0.35), and significantly negatively correlated with FRAUD (–0.28), providing preliminary support that deeper big-data adoption improves monitoring efficiency, enhances report quality, and suppresses fraud. Size correlates positively with ICM, while leverage has slight negative correlations with ICM and FRQ, underscoring the need to control for these factors in regressions.

Table 1. Descriptive Statistics and Correlations

Variable	Mean	Std. Dev.	Min	Max	Corr(BDI)	Corr(ICM)	Corr(FRQ)	Corr(FRAUD)
BDI	0.45	0.20	0.10	0.90	1.00	0.42	0.35	–0.28
ICM	2.10	0.55	0.50	3.50	0.42	1.00	0.30	–0.22
FRQ	0.72	0.18	0.30	0.98	0.35	0.30	1.00	–0.25
FRAUD	0.15	0.22	0.00	1.50	–0.28	–0.22	–0.25	1.00
Size (log Total Assets)	21.50	1.10	18.00	24.80	0.20	0.25	0.15	–0.10
ROA	0.08	0.05	–0.10	0.20	0.12	0.18	0.10	–0.05
Leverage	0.45	0.15	0.10	0.80	–0.10	–0.08	–0.12	0.05

These initial results suggest strong positive associations between big-data adoption and both monitoring capability and reporting quality, and a negative association with fraud risk. We proceed to test the statistical significance and causal direction of these relationships, controlling for other factors.

5.2 Regression Analysis and Robustness Tests

Using firm and year fixed-effects panel regressions with robust standard errors, we find that BDI exerts a highly significant positive effect on ICM and FRQ, and a significant negative effect on FRAUD as shown in Table 2. Specifically, a one-standard-deviation increase in BDI raises ICM by 0.28 units ($p < 0.01$), increases FRQ by 0.19 units ($p < 0.05$), and reduces FRAUD by 0.12 incidents ($p < 0.05$).

We conduct three robustness checks. First, industry-level big-data infrastructure investment intensity serves as an instrument for BDI in two-stage least squares; the core coefficients remain consistent in sign and significance. Second, subsample regressions by ownership (state vs. non-state) and size (large/medium vs. small) show slightly higher BDI effects in state-owned and larger firms, but the overall pattern holds. Third, replacing ICM with the annual count of risk warnings and FRAUD with the frequency of major misconduct incidents yields similar results. These findings confirm that big data finance reliably enhances monitoring efficiency, report quality, and fraud prevention.

Table 2. Fixed-Effects Regression Results

Variable	ICM (Model 1)	FRQ (Model 2)	FRAUD (Model 3)
BDI	0.28*** (0.05)	0.19** (0.08)	–0.12** (0.06)
Size	0.07** (0.03)	0.05 (0.04)	–0.02 (0.02)
ROA	0.11*** (0.02)	0.08** (0.03)	–0.05* (0.03)
Leverage	–0.04 (0.03)	–0.06* (0.03)	0.03 (0.02)
SOE	0.09* (0.05)	0.07 (0.06)	–0.08* (0.04)
Indep	0.06 (0.04)	0.04 (0.05)	–0.03 (0.03)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	7,200	7,200	7,200

6. Discussion and Managerial Implications

6.1 Interpretation of Research Findings

Empirical results show that the application of big data in finance has significantly enhanced the real-time monitoring capabilities of enterprises' internal control. This finding verifies the theoretical value of the "in-process monitoring + pre-event early warning" model from multiple perspectives. Firstly, through quantitative examination of dimensions such as annual report keywords and the number of warnings, we found that the big data platform can quickly capture signals such as budget execution deviations and abnormal transactions, enabling management to respond promptly and significantly reducing the average response time for internal control deficiencies. This not only reduces the decision-making errors caused by information lag, but also promotes enterprises to maintain an efficient risk prevention and control rhythm in a dynamic environment. Secondly, the visual dashboard and risk scoring model empowered by big data technology provide intuitive and traceable decision-making basis for the internal audit and finance departments, enhancing the transparency and credibility of the supervision process, and further consolidating the closed-loop operation of the internal control system.

Meanwhile, the positive impact of big data finance on the quality of financial reports and its negative inhibitory effect on fraud risks reveal the crucial role of technical supervision in enhancing the authenticity and completeness of information disclosure. Empirical regression shows that for every one standard deviation increase in BDI, the abnormal fluctuations of attributable accrual profits significantly decrease, and the interpretability and consistency of financial reports are enhanced. The frequency of fraud incidents has decreased significantly. This indicates that when the management formulates and discloses financial information, real-time early warning and cross-verification of multi-source data can form a powerful check and balance mechanism, reducing the space for subjective manipulation and illegal disclosure. Further grouped regression and substitution index tests also indicated that this supervisory effect was particularly prominent in state-owned enterprises and large and medium-sized enterprises, suggesting that organizational scale and governance structure have a moderating effect on the application effect of big data. Overall, big data finance, by strengthening process monitoring and result feedback, injects the ability of continuous optimization and self-correction into enterprise financial decision-making, which has profound significance for improving financial management levels and maintaining market trust.

6.2 Suggestions for Enterprise Practices and Supervision

Based on the above research findings, enterprises should promote the in-depth application of big data finance simultaneously from both technical and organizational aspects. At the technical level, efforts should be made to continuously improve the construction of the big data middle platform and real-time stream processing platform, and build a unified data aggregation and analysis framework to ensure that data from key links such as transactions, budgets, and audits can be seamlessly integrated and promptly mined and visually displayed. At the same time, enterprises should establish and improve a data governance system, strictly regulate data quality, semantic standards and permission management, and prevent the risks of data silos and abuse. On this basis, promote cross-departmental collaboration, strengthen the coordination mechanism among the finance, risk control, IT and audit teams, so that the results of data analysis can be promptly fed back into the decision-making process, truly achieving a closed-loop operation of "in-process monitoring - decision optimization - risk early warning - effect evaluation".The regulatory authorities should actively play a guiding and regulatory role to provide institutional guarantees for the healthy development of big data finance. Firstly, regulatory authorities can formulate data standards and compliance guidelines, putting forward clear requirements for privacy protection and security control during the collection, transmission, storage and use of financial data, and promoting the formation of unified technical norms and best practices within the industry. Secondly, the application of regulatory technology (RegTech) in auditing and compliance checks should be encouraged. Under the premise of carefully assessing risks, necessary data interfaces should be opened to support banks, listed companies and fintech enterprises in conducting regulatory sandbox tests in a safe and controllable manner to verify the effectiveness and feasibility of new technologies in financial supervision. Finally, regulatory authorities can enhance the continuous assessment and dynamic adjustment of the application effects of big data technology. By means of annual disclosure, case analysis, etc., they can share typical experiences and urge market entities to constantly optimize their internal control and decision-making processes. This will not only improve the efficiency of supervision but also create a fair and transparent market environment.

7. Conclusion

Using panel data from Chinese A-share firms (2018–2023), this study systematically examines how big data finance supports and supervises corporate financial decision-making. Enhanced big-data adoption significantly improves real-time internal-control monitoring, accelerates responses to anomalies, raises financial reporting authenticity, and effectively suppresses fraud. These findings validate the “real-time monitoring + early warning” paradigm and highlight the transformative impact of big-data technology on financial governance and risk management.Nevertheless, our research has limitations. First, our BDI relies on annual-report disclosures and keyword frequencies, which may not fully capture the depth of big-data initiatives. Second, focusing on Chinese listed firms may limit generalizability to other regulatory environments. Third, while instrumental variables and subsample tests mitigate endogeneity, some bias may remain due to data constraints. Future studies could explore cross-country samples to test universal applicability and incorporate finer-grained operational data (e.g., warning-log records) to refine measurement. Examining how organizational culture and technology maturity moderate supervisory effectiveness also warrants further investigation. We hope our findings inform firms in building dynamic, traceable decision loops and assist regulators in advancing a technology-driven supervisory framework.

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