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Chapter: Transforming Organizational Systems Through Innovation Management and Digital Capability Building

HOW ENTERPRISE DIGITAL TRANSFORMATION RESHAPES RISK SHARING BETWEEN BANKS AND ENTERPRISES: BASED ON MULTIPERIOD DID ANALYSIS

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Annotation. The digital transformation of enterprises is seen as a key variable in reshaping bank–enterprise relationships and enhancing a financial system's resilience. However, the literature has rarely provided a systematic explanatory framework or theoretical mechanisms for how and whether it alters the risk-taking behavior between banks and enterprises. Drawing on theories of information asymmetry and financing constraints, using the data from nonfinancial listed companies on China's A-share market from 2013 to 2021, a multiperiod difference-in-differences model was employed to explore how corporate risk-taking influences bank risk-taking, and the heterogeneous effects were examined based on enterprises' level of digital transformation, R&D investment, and information transparency. Results reveal that corporate risk-taking has a significant inhibiting effect on bank risk-taking, exhibiting a clear inverse change. Furthermore, the results after incorporating the effects of digital transformation reveal that corporate risk-taking has a significant promoting effect on bank risk-taking, leading to a clear positive change. In particular, corporate risk-taking influences bank risk-taking through the mechanisms of information asymmetry and financing constraints, serving as a mediating effect. The degree of competition between enterprises also plays a significant positive moderating role between corporate and bank risk-taking, thereby enhancing the promoting effect of corporate risk-taking on bank risk-taking. Furthermore, the influence of corporate risk-taking on bank risk-taking is heterogeneous, and enterprises with higher digital transformation levels, more R&D investment, and better information transparency have a more pronounced positive promoting effect. The conclusions provide decision-making support for the coordinated promotion of bank–enterprise risk-sharing through digital transformation.

Keywords: enterprise digital transformation, bank risk-taking, corporate risk-taking, multiperiod DID, changes in bank-enterprise risk-sharing.

JEL classification: G21, O33, D82.

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Introduction

Enterprises are not only the core entities driving the modern market economy but also the primary bearers of financial risks. Their risk-taking behavior affects not just their operational resilience and access to financing but also the stability of the entire financial system and its ability to prevent systemic risks at a broader level. From a global perspective, countries have increasingly emphasized the coordination between high-quality economic development and financial security in recent years. For instance, the 2025 China Government Work Report calls for "effectively stimulating the vitality of various business entities, gradually resolving risks during development, and achieving a positive interaction between high-quality development and high-level security," indicating that enterprises must elevate their risk awareness and risk management capabilities to a strategic level under the highly uncertain global macroeconomic environment. By optimizing operational decisions and resource allocation, firms can enhance competitiveness while strengthening collaboration with various financial and industrial entities, thereby promoting the parallel development of risk governance and innovation and maintaining overall economic and financial resilience. At the same time, in many emerging economies and some developed economies, the enterprise-driven structure of the real economy and the bank-driven financing system are still prevalent. Bank credit remains the most important source of external financing for enterprises. Some changes in bank credit standards, loan size, and risk preferences not only directly affect the availability of financing and cost of funds but also transmit potential risks between banks and enterprises through balance sheet connections. This scenario can lead to debt expansion and resource misallocation, as well as cause regional or even systemic financial risks under amplification mechanisms (Nguyen, Ho, 2024). In this context, the accelerated digital transformation of enterprises is profoundly reshaping the mechanisms of risk identification, risk pricing, and risk-sharing between banks and enterprises. However, several critical questions still require systematic examination: (1) how does enterprise digital transformation alter the dynamic interaction of risk-sharing between banks and enterprises? (2) Under what conditions can this relationship evolve from "risk misalignment" to "joint risk-sharing?" (3) Can this process alleviate corporate financing constraints and enhance the resilience of the financial system? These questions are of significant theoretical importance, and their answers offer practical insights for global financial risk governance and resource optimization in the context of the digital economy.

Existing research mainly explains changes in the risk-sharing relationships between banks and enterprises from three theoretical perspectives. First, from the perspective of internal value empowerment theory, digital technologies, such as big data, cloud computing, and blockchain, reconstruct enterprise production processes and management models. These technologies not only improve resource allocation efficiency and operational performance but also reshape the enterprise's risk identification, measurement, and management systems. This, in turn, alters the structure of the enterprise's demand for credit resources and risk-taking preferences under risk-return trade-offs, influencing the way risk-sharing is linked between banks and enterprises (Yuan, 2022; Delis *et al*., 2023). Second, from the perspective of external value empowerment and financial intermediary function theory, digital transformation reduces information asymmetry and credit allocation imbalance between banks and enterprises by establishing supply chain financial platforms, data-sharing platforms, and intelligent risk control systems. This transformation drives the shift in bank credit from being "collateral-driven" to "data-driven," thereby improving financing accessibility and pricing efficiency, while also potentially altering the coupling of risk exposure and risk-bearing pace between banks and enterprises (Lei *et al*., 2024; Ozgur *et al*., 2021). Third, from the perspective of risk transmission and market competition theory, digitalization enhances risk monitoring and compliance management through various mechanisms, such as algorithmic decision-making and smart contracts, thus improving the resilience of the financial system. Under intense

competition and high-pressure transformation investments, issues such as algorithmic bias, system vulnerabilities, and data leaks may arise, potentially forming a path from high-leverage expansion to risk accumulation and then to capital stress, thus reshaping the risk-sharing or misalignment structure between banks and enterprises (Jing, 2023; Eguren-Martin *et al*., 2024).

Unfortunately, existing studies focus on the single-subject impact of digital transformation on corporate performance, risk management capabilities, or bank credit allocation efficiency. These studies often analyze risk-taking behavior changes from either the enterprise side or the bank side and pay limited attention to the dynamic evolution process of the "bank–enterprise relationship" as a risk-sharing system. Specifically, most studies stay at the level of individual bank or enterprise subjects and lack a micro-path depicting the interactive and dynamic evolution of risk-sharing between the two from the perspective of the overall bank–enterprise relationship. Furthermore, there is a lack of a rigorous, testable framework as well as systematic empirical evidence on how digital transformation changes the information structure and financing constraints between banks and enterprises, and how this process promotes a shift in risk-sharing behavior from inverse changes to joint changes. Moreover, few studies systematically examine the potential boundary effects and differentiated impacts of heterogeneous characteristics, such as enterprise competition levels, the depth of digital transformation, R&D investment intensity, and information transparency. To address these gaps, this study introduces the theories of information asymmetry and financing constraints as the main analytical frameworks to explain how enterprise digital transformation reshapes the bank–enterprise risk-sharing relationship. In accordance with information asymmetry theory, differences in information ownership, disclosure, and interpretation between banks and enterprises directly affect credit pricing and risk-sharing structures. By improving data accessibility and information transparency, enterprise digital transformation is expected to reduce the information distance between banks and enterprises, thereby weakening adverse selection and moral hazard and eventually increasing the possibility of joint risk-sharing (Vanhaverbeke *et al*., 2024). Under the framework of financing constraint theory, the external financing cost being higher than the internal financing cost is a key factor restricting corporate risk-taking and investment decisions. Digital transformation can alleviate financing constraints by expanding financing channels and innovating financial products and services. Moreover, it changes how banks assess the creditworthiness and project risks of enterprises, thus affecting the proportion and direction of risk-bearing between banks and enterprises in the risk-return framework (Yan and Ling, 2025). Unlike previous studies that treat information asymmetry and financing constraints as isolated preconditions, this study views them as two interconnected and complementary mechanisms. On the one hand, information asymmetry is an important "upstream cause" of financing constraints. The more opaque the information structure between banks and enterprises, the more likely banks are to tighten credit constraints by increasing risk premiums and reducing credit limits. On the other hand, financing constraints are the direct carriers and practical manifestations of the effects of the information structure on the bank–enterprise risk-sharing relationship. When external financing is limited and marginal financing costs are high, even high-return projects cannot effectively increase the level of risk-taking. As such, information asymmetry and financing constraints logically present a chain transmission relationship from the information structure to financing constraints and then to risk-taking. They also form two complementary paths through which digital transformation affects the bank–enterprise risk relationship. In particular, digital transformation can directly reduce adverse selection and moral hazard by improving the information environment, and it can also indirectly enhance the degree of joint risk-sharing between banks and enterprises by alleviating financing constraints. Based on this understanding, this study focuses on the interactive relationship between the "information asymmetry

mechanism" and the "financing constraint mechanism" in the subsequent theoretical analysis and hypothesis testing.

Given the abovementioned information, this study aims to explore the following research questions based on the perspectives of information asymmetry theory and financing constraint theory: (1) Does a stable association pattern exist between bank and enterprise risk-sharing in real credit relationships, and will enterprise digital transformation significantly alter this pattern, even transitioning from "risk misalignment" to "joint risk-sharing"? (2) Does enterprise digital transformation promote a shift in the risk-sharing relationship from inverse changes to joint changes by alleviating information asymmetry and financing constraints between banks and enterprises, and what are the specific mechanisms at play? (3) Under different levels of enterprise competition, digital transformation depth, R&D investment intensity, and information transparency, does digital transformation have significantly heterogeneous impacts and boundary conditions on the bank–enterprise risk-sharing relationship, thus providing targeted policy recommendations for the differentiated promotion of enterprise digital transformation and bank–enterprise risk management collaboration?

The marginal contributions of this study are mainly reflected in the following three aspects: (1) Transitioning from "single-party risk" to an overall depiction of "bank–enterprise relationship risk," expanding the analytical framework for research on bank–enterprise risk interactions. Existing studies often focus on the perspectives of banks or enterprises, examining either commercial bank risk-taking or corporate risk-taking, with insufficient attention paid to the risk symbiosis, risk misalignment, and their dynamic evolution formed under credit contracts between the two parties. This study extends the research perspective from a single economic entity to the bank–enterprise relationship, systematically depicting the linkage logic and evolution path of risk-taking between banks and enterprises based on information asymmetry and financing constraint theories. This study also identifies the structural differences in risk-taking dynamics before and after digital transformation—showing "inverse change" before and "joint change" after digital transformation. This finding provides a new, holistic research framework for understanding the intrinsic operational mechanisms of the bank–enterprise risk relationship.

(2) Constructing the micro-transmission mechanism of the "digital transformation - information asymmetry/financing constraints - bank–enterprise risk-taking relationship," deepening the theoretical explanation of how digital transformation reshapes the bank–enterprise risk paradigm. Although existing literature emphasizes that digitalization helps alleviate information asymmetry and improve the financing environment, most studies remain at a qualitative analysis level and lack testable frameworks for identifying mechanisms. In comparison, this study introduces enterprise digital transformation into the bank–enterprise risk interaction model under the umbrella of information asymmetry and financing constraint theories. It focuses on two main lines: improving information transparency and alleviating financing constraints. Furthermore, this study systematically examines how digital transformation drives the shift in the bank–enterprise risk-taking relationship from "inverse change" to "joint change" and further identifies the moderating effect of enterprise competition intensity on this process. This micro-mechanism analysis reveals the dual effects of digital transformation, which "reshapes the risk-sharing structure and changes the risk linkage direction," thus providing more practical theoretical support for banks in optimizing credit allocation and for enterprises in solving financing difficulties.

(3) Building multidimensional heterogeneity response paths and improving the differentiated policy logic for the collaboration between digital transformation and bank–enterprise risk management. Existing research often views digital transformation as a homogeneous shock and overlooks significant differences in enterprises' technological foundations, innovation investments, and information governance. This study

identifies the boundary conditions and differentiated effects of digital transformation on the bank–enterprise risk-taking relationship based on three characteristics: the depth of digital transformation, R&D investment intensity, and information transparency. The study finds that enterprises with higher digital transformation levels, more R&D investments, and better information transparency exhibit more significant joint changes in bank–enterprise risk-taking. This finding not only provides direct evidence for enterprises to assess their own risk-bearing capacity and optimize the pace of digital investment and financing strategies but also offers important references for regulators and financial institutions to implement differentiated and tiered bank-enterprise risk management policies during the digitalization process. Doing so helps stimulate enterprise vitality and promotes high-quality economic development under controllable risks.

1. Theoretical Analysis and Hypothesis Development

1.1 Changes in the Bank–Enterprise Risk-Taking Relationship

In a financing system characterized by a "bank-dominated" model, bank credit remains the most important external financing source for enterprises. The way credit is allocated directly affects the risk exposure and operational resilience of the real economy (Ben Ameur *et al*., 2024). Information asymmetry theory posits that differences in information possession, disclosure, and interpretation between banks and enterprises systematically reflect varying degrees of risk aversion in credit approval, pricing, and contract constraints. Enterprise management is more familiar with the quality and risk-return structure of their projects, while banks are often at an informational disadvantage. This can lead them to overestimate the probability of bad projects and underestimate the value of good projects. Consequently, banks engage in "defensive pricing" by raising risk premiums, tightening credit limits, and shortening loan terms (Vanhaverbeke *et al*., 2024).

Within the abovementioned framework, when enterprises proactively increase their risk-taking levels based on their informational advantage to pursue higher returns, banks passively strengthen their risk controls and reduce their risk exposure out of concern for "adverse selection" and "moral hazard." This creates an inverse "reverse adjustment" mechanism, wherein enterprise risk increases while bank risk decreases. Consequently, risk-sharing between banks and enterprises shows a reverse change relationship (Kabir *et al*., 2022). From the perspective of financing constraint theory, the external financing cost is systematically higher than the internal financing cost.

Additionally, under conditions of information asymmetry, banks tend to impose stricter credit constraints on enterprises with higher risks. Enterprises seeking to expand investments, increase R&D, or undertake high-risk projects often face the triple pressure of high risk, high costs, and tight constraints (Li *et al*., 2025). On the one hand, when enterprises increase their risk-taking to pursue growth opportunities, banks are likely to raise interest rates, add collateral requirements, and impose restrictive clauses to hedge against potential default losses. This shifts part of the risk costs to enterprises, subjecting them to higher financial pressure and refinancing uncertainty. On the other hand, when banks raise risk capital requirements or reduce the proportion of high-risk assets to comply with regulatory constraints or internal prudent management goals, they suppress enterprises' further leveraging behavior through price and limit adjustments, thereby "pushing" the systemic risk back onto the enterprises' balance sheets (Cowling, Yang, 2024; Cathcart *et al*., 2024). Therefore, when enterprises have not yet undergone digital transformation, the information gap between banks and enterprises is relatively large, and financing constraints are common. As a result, bank–enterprise risk-sharing often adjusts in reverse, with banks tightening their risk exposure when enterprise risk increases; at the same time, banks passively increase

risk exposure under counter-cyclical policies or regulatory guidance when enterprises become more conservative. This scenario leads to a macro-level reverse change in the bank–enterprise risk-taking relationship. Based on the combined effects of information asymmetry and financing constraints, the following hypothesis can be proposed:

Hypothesis 1: Before the digital transformation of enterprises, corporate risk-taking has an inhibiting effect on bank risk-taking. Therefore, risk-taking between banks and enterprises shows a reverse change trend.

1.2 Changes in the Bank–Enterprise Risk-Taking Relationship after Digital Transformation

After an enterprise completes its digital transformation, the institutional environment of both banks and enterprises undergoes a systematic restructuring in terms of information structure and financing constraints. This provides the theoretical foundation for the transformation of the bank–enterprise risk-sharing relationship from "misaligned hedging" to "joint risk-sharing." Information asymmetry and financing constraint theories argue that digital transformation not only changes the patterns of information possession, disclosure, and interpretation between banks and enterprises but also reshapes the external financing cost structure and credit constraint boundaries. Consequently, it may enable higher levels of coordinated adjustment between banks and enterprises in the risk-return space (Shen *et al.*, 2025).

Furthermore, information asymmetry theory posits that, when banks are at an informational disadvantage, they often hedge against potential high-risk behavior by enterprises by increasing risk premiums, strengthening collateral requirements, and setting stricter contractual terms. This strategy creates a reverse adjustment pattern in which enterprise risk rises while bank risk contracts (Kwon, 2022). Enterprise digital transformation integrates and structures previously scattered multisource data from internal management systems, supply chain nodes, customer behaviors, and unstructured texts using technologies like big data, cloud computing, and artificial intelligence. Through digital reports and online disclosure platforms, it significantly improves the accessibility and verifiability of information, thus reducing the information distance between banks and enterprises (Nishitani *et al.*, 2025). In this process, banks no longer rely solely on outdated financial reports and limited collateral information. Instead, they can conduct more dynamic and precise assessments of enterprise profitability and default risks based on real-time operational, transaction, and behavioral data. In this way, the information advantage shifts from being "static and one-sided" to "dynamic and panoramic" (Wang *et al.*, 2023).

Furthermore, the alleviation of information asymmetry weakens banks' overly cautious stance toward high-risk projects, reducing the need to rely solely on conservative pricing and shrinking credit limits for risk management. On the other hand, it encourages enterprises to expose more accurate operational information to bank supervision, enhancing the endogenous constraints of risk management under "visualized" constraints (Castiglionesi and Zhao, 2024). As a result, banks are better positioned to increase credit support intensity while ensuring risk control. Enterprises, based on more transparent data, can also form a "synchronized decision-making" risk-taking logic, which means that when enterprises increase risk-taking based on real information to seize growth opportunities, banks will also increase their risk exposure. Additionally, banks will match support in terms of credit scale and term structure, resulting in synchronized changes in bank–enterprise risk-sharing.

Under the framework of financing constraint theory, the external financing cost for enterprises is systematically higher than the internal cost of funds. This is a major factor that suppresses high-risk investments and limits their risk-taking capacity (Grundy and Verwijmeren, 2020). Traditionally, under the dual constraints of information asymmetry and regulatory pressure, banks often compensate for risks by raising loan interest rates, adding strict guarantees, and imposing contractual terms. While this practice

may limit banks' risk exposure on paper, it raises the marginal financing costs for enterprises. This, in turn, exacerbates the issue of difficult and expensive financing for enterprises, forcing them to adopt a conservative approach to high-risk projects. This creates a misalignment pattern in which "enterprise risk willingness is suppressed, and bank risk exposure increases or shifts passively" (ElFayoumi, 2024). Enterprise digital transformation, on the one hand, broadens financing channels through financial technology tools, including supply chain finance platforms, online lending, and data asset pledges, thereby improving the efficiency of financing transactions and risk control levels. On the other hand, digital transformation enhances the traceability and verifiability of operational data, enabling banks to price and extend credit based on more measurable risks and predictable cash flows. This effectively reduces the risk premium caused by information asymmetry and improves credit allocation efficiency (Fernandes *et al*., 2021). In this environment of digital cost reduction and efficiency improvement, the marginal external financing cost for enterprises decreases, and credit availability increases, providing them with greater financial flexibility to take on high-risk, high-return projects, such as R&D investments, technological upgrades, and market expansion (Liu and He, 2024).

At the same time, supported by digital risk control and data-driven credit extension, banks can moderately expand the scale of risk assets for digital enterprises without significantly increasing the unit risk cost. This means that as enterprises increase their risk-taking, bank risk exposure also rises. However, this rise occurs under conditions of "more complete information and finer constraints," achieving "rational risk-sharing" (Chen *et al*., 2024). Therefore, once digital transformation alleviates financing constraints and alters the risk-return trade-off boundaries, banks and enterprises are more likely to form a risk-reward sharing cooperative equilibrium: When enterprises increase risk investments, banks simultaneously increase credit support and risk exposure; when enterprises reduce risk exposure, banks adjust their risk asset allocations accordingly. This overall dynamic shows a synchronized adjustment in risk-taking between banks and enterprises. Based on the dual perspectives of information asymmetry and financing constraints, the following hypothesis can be proposed:

Hypothesis 2: After the digital transformation of enterprises, corporate risk-taking has a promoting effect on bank risk-taking. Therefore, risk-taking between banks and enterprises shows a trend of synchronized changes.

1.3 The Mechanisms through Which Enterprise Digital Transformation Affects Changes in the Bank–Enterprise Risk-Taking Relationship

Information asymmetry and financing constraints are not independent environmental conditions; rather, they present a hierarchical relationship that flows from upstream information structure to midstream financing constraints and downstream risk-taking. On the one hand, the asymmetry in information possession and disclosure between banks and enterprises is a key trigger for commercial banks to implement cautious pricing and increase collateral requirements. It is also the root cause of enterprises facing systematically higher external financing costs. On the other hand, the credit rationing and financing constraints formed by banks based on this asymmetry directly determine whether and to what extent enterprises can translate their risk preferences into actual risk-taking behaviors. Therefore, from a mechanistic perspective, the impact of enterprise digital transformation on the bank–enterprise risk-taking relationship involves at least two interconnected but distinct transmission paths. One path is from digital transformation to the alleviation of information asymmetry and then to bank–enterprise risk coordination. This occurs by improving the authenticity, timeliness, and verifiability of operational data, thus reducing the information distance between banks and enterprises and changing the way the former perceives and prices enterprise risks.

The other path is from digital transformation to the improvement of financing constraints and then to bank–enterprise risk coordination. This path occurs by expanding financing channels, reducing marginal financing costs, and enhancing the financial flexibility of enterprises to take on risk assets and high-risk projects. The former path emphasizes the reshaping of the information structure by digital transformation, while the latter highlights its role in loosening resource constraints. Together, these two paths form a complementary mechanism framework through which enterprise digital transformation reshapes the bank–enterprise risk paradigm. Based on this overall framework, this study proposes corresponding research hypotheses from the perspectives of the information asymmetry mechanism and the financing constraint mechanism, details of which are shown below.

1.3.1 Information Asymmetry Mechanism

Information asymmetry is a common phenomenon between market entities due to differences in information access costs, levels of information disclosure, and information interpretation abilities (Zhu *et al.*, 2022). In particular, in a bank–enterprise relationship, when one party has better or more information than the other, or when an enterprise does not fully disclose its financial condition, operational risks, and other information, banks may not fully understand the true situation of the enterprise. This asymmetry leads to uncertainty in risk assessment and increases the level of bank risk-taking. Enterprise digital transformation can more effectively collect, process, and share data. Through data analysis and reporting, enterprises can improve internal and external information transparency, reducing information asymmetry. Banks can also more easily access accurate enterprise data, which increases mutual risk-taking levels (Liang and Zhang, 2024).

This study specifically examines three aspects: data acquisition, processing efficiency, and information integration. First, digital transformation not only improves the frequency and quality of enterprise information disclosure but also facilitates the structuring of unstructured data, such as consumer behavior, supply chain dynamics, and managerial language characteristics, using technologies like artificial intelligence (AI) and big data. This breaks the limitations of traditional financial statements and provides banks with a more comprehensive, real-time operational profile of the enterprise (He *et al.*, 2024). Second, the information flow under digital systems has higher accuracy and timeliness, allowing banks to reduce inaccurate judgments caused by delayed or distorted information when conducting credit assessments and loan decisions. This reduces errors in credit rationing and increases the likelihood of risk coordination between banks and enterprises (Jaskowski and Rettl, 2023).

Additionally, while improving the level of data sharing, digital platforms also enhance the enterprise's acceptability of external supervision. This forces enterprises to improve the transparency and standardization of their operations. Especially with the support of traceable technologies like blockchain, the past "information black box" of enterprises is gradually being opened, providing banks with higher-quality external governance clues and effectively alleviating adverse selection and moral hazard issues (Ballew and Sheneman, 2025). Therefore, by improving the accessibility, interpretability, and verifiability of information, digital transformation not only reduces the information gap between banks and enterprises but also provides the conditions to build a data-driven trust mechanism. This scenario ultimately achieves synchronized resonance in risk-taking between banks and enterprises. Thus, the study proposes the following hypothesis:

Hypothesis 3: After the digital transformation of enterprises, corporate risk-taking positively promotes bank risk-taking by reducing information asymmetry.

1.3.2 Financing Constraint Mechanism

The financing constraints faced by enterprises are largely due to the shortage of internal investment funds caused by the higher external financing costs compared to internal financing costs (Naeem and Li, 2019). Domestic and international scholars agree that the issues of difficult and expensive financing restrict enterprises from investing in high-risk projects, which in turn affects their risk-taking levels (Yin *et al*., 2022). Through the use of information technology, digital transformation stimulates new momentum for cost-seeking, bridging the information gap created by the market. Such transformation also expands the financing channels between banks and enterprises, strengthens the resilience of the financial relationship, alleviates the imbalances caused by credit rationing between banks and enterprises, and effectively reduces the financing constraints of enterprises. These, in turn, raise the risk-taking levels of enterprises while leading to an increase in bank risk-taking, thus promoting the synchronized growth of risk-taking between the two (Zhang *et al*., 2023).

Therefore, the role of enterprise digital transformation in alleviating financing constraints and promoting a "shared fate" mechanism in bank–enterprise risk-taking can be further analyzed from two perspectives: financing channel diversification and fund allocation efficiency. First, through financial technology, enterprise digital transformation breaks the traditional, single-channel banking lending path. It also provides enterprises with broader access to information and more efficient platforms for matching funds, such as supply chain finance, internet financial platforms, and equity crowdfunding, among other new financing methods (Tian and Su, 2024). The diversification of financing channels effectively increases the proportion of direct financing and digital financial services. While dispersing enterprise financing risks, it also enhances the enterprise's financing capacity, making them more proactive in taking on venture investments. At the same time, the diversification of financing channels improves the transparency of risk information between banks and enterprises. In particular, banks can more accurately assess enterprise operational risks, thus gaining confidence to increase loan supply to enterprises, which in turn, raises the risk-taking levels of banks (Li *et al*., 2025).

Second, relying on technologies such as big data and AI, digital transformation enhances the efficiency of fund allocation in investment and financing activities between banks and enterprises (Lăzăroiu *et al*., 2025). Specifically, enterprises can monitor real-time fund usage and project risk levels, using data analysis to improve the accuracy of risk assessments, reduce risk pricing costs and capital monitoring costs, and increase the precision of fund matching between banks and enterprises. This improvement in fund allocation efficiency not only alleviates enterprise financing constraints but also fosters a positive interactive mechanism for risk-sharing between enterprises and banks, thus strengthening the synchronization of risk-taking between them. Therefore, the study proposes the following hypothesis:

Hypothesis 4: After the digital transformation of enterprises, corporate risk-taking positively promotes bank risk-taking by alleviating financing constraints.

1.3.3 The Moderating Effect of Enterprise Competition on Changes in the Bank–Enterprise Risk-Taking Relationship

From the perspective of information asymmetry theory, the level of competition in the industry in which an enterprise operates considerably affects the quality of the information structure between banks and enterprises, as well as the marginal value of digital information. In highly competitive industries, enterprises often implement more aggressive business strategies through price wars, frequent product iterations, and high capital expenditures to gain and maintain market share within a limited market space.

This strategy results in greater volatility and uncertainty in their operational cash flow and profitability (Miao *et al*., 2022; Kim and Lee, 2023). In such a high-uncertainty environment, traditional credit models that rely on static financial statements and soft information cannot effectively identify the true quality of enterprises. Furthermore, the level of information asymmetry between banks and enterprises is higher, and banks tend to rely on "conservative credit" to hedge against potential risks. At this point, when enterprises pursue digital transformation and provide banks with more frequent, granular, and traceable operational data, it significantly improves the accessibility and verifiability of information. This, in turn, converts the noise information that was previously mixed in high-frequency fluctuations into effective information that can be analyzed by algorithms and identified by risk control models.

As for banks, digital data have a greater marginal contribution to reducing adverse selection and moral hazard within industries with more intense competition and harder-to-assess risks, thereby alleviating the residual information asymmetry. This encourages banks to shift from defensive credit to selective offensive credit based on data support, thereby strengthening risk-sharing and credit support for high-quality digital enterprises. In other words, in highly competitive industries, the effect of digital transformation on reducing information asymmetry is more significant, and its role in promoting synchronized changes in risk-taking between banks and enterprises is amplified.

Meanwhile, from the perspective of financing constraint theory, the higher the competition level within an industry, the more its profit margins and internal capital accumulation capacity are compressed, leading to increased reliance on external financing. Under traditional financing conditions, when banks face enterprises in highly competitive industries with significant profit fluctuations, they often raise risk premiums, strengthen collateral, and impose restrictive clauses due to prudential considerations. This move creates a path from high competition to high premiums to high constraints, ultimately making it difficult for enterprises to convert their risk preferences into actual risk-taking, even when high-return projects exist. In such a scenario, digital transformation helps alleviate financing constraints by constructing diversified financing channels, such as supply chain finance platforms, online lending, and data asset pledging. In this regard, using technologies like big data and cloud computing can significantly improve the precision of enterprise credit assessments and fund allocation efficiency, thereby reducing the risk premiums caused by information asymmetry and industry uncertainty (Tian and Su, 2024; Lăzăroiu *et al*., 2023).

As for enterprises in highly competitive industries with higher reliance on external financing, the marginal effect of digital transformation in alleviating financing constraints is more pronounced. On the one hand, the reduction in external financing costs is greater, and credit availability is improved, thus providing enterprises with greater financial flexibility to undertake high-risk, high-return projects. On the other hand, under the support of digital risk control and regulatory compliance, banks are more motivated to expand their risk asset exposure to these enterprises. Thus, when enterprises increase their risk-taking, banks will raise their own risk exposure in parallel, forming a dynamic linkage of shared risk-rewards.

In contrast, in industries with higher levels of monopoly and insufficient competition, enterprises tend to have more stable profits and stronger bargaining power. Even if the digital transformation level is not high, they can still obtain financing support through relationship-based lending, implicit guarantees, or soft budget constraints. Banks can also rely on long-term relationship information and regulatory exemptions to assess the risks of these enterprises, which means that the marginal improvement of digital transformation in alleviating information asymmetry and financing constraints is relatively limited (Orden-Cruz et al., 2023). In such environments, even if enterprises undergo digital transformation, the influence of the newly generated data signals on bank credit decisions and risk preferences is relatively weak.

Furthermore, the magnitude of the shift from "reverse change" to "synchronized change" in risk-taking is relatively small.

In summary, from the dual perspectives of information asymmetry and financing constraints, it can be inferred that as the level of competition among enterprises increases, digital transformation strengthens the mechanism that drives the shift from "reverse change" to "synchronized change" in bank–enterprise risk-taking by improving the information structure between banks and enterprises and significantly alleviating financing constraints in high-competition contexts. In contrast, in industries with higher monopolistic levels and insufficient competition, this positive effect is relatively weakened. Therefore, the more competitive the industry, the stronger the promoting effect of digital transformation on synchronized changes in bank–enterprise risk-taking. Hence, this study proposes the following hypothesis:

Hypothesis 5: After the digital transformation of enterprises, the level of competition in enterprises plays a positive moderating role in the relationship between corporate risk-taking and bank risk-taking.

2. Methodology

2.1 Sample Selection and Data Sources

This study aims to explain the impact of corporate risk-taking on bank risk-taking before and after the treatment effect of enterprise digital transformation. Given data availability, the study selected nonfinancial listed companies on China's A-share market and corresponding bank data from 2013 to 2021 to construct panel data for empirical analysis. Data from 2021, 2022, and 2023 were used to calculate the 2021 corporate risk-taking level, so 2022 and 2023 data were excluded from the study. Given that loans are a crucial bridge connecting banks and enterprises, and bank loans to enterprises better reflect changes in risk-taking between banks and enterprises, this study used data on bank loans to listed companies to weigh the bank risk-taking variable. The data came from the China Stock Market and Accounting Research (CSMAR) database on listed company loans. Therefore, this study matched loan information from each bank with the annual data of A-share listed companies, resulting in 215,756 loan records.

The specific procedure can be described as follows: First, loan records were organized into a dataset of enterprise-year-bank name-loan size, which was then matched with the bank's historical risk-taking levels. Next, the data were weighted by loan size at the enterprise level, producing a panel dataset of enterprise-year-weighted bank risk-taking level. To ensure the robustness of the research results, the panel data were processed as follows: (1) enterprises in ST (Special Treatment) or PT (Particular Treatment) status were excluded, (2) all financial enterprises were excluded, (3) enterprises with missing data for related variables were removed (the enterprise-related data also came from the CSMAR database), and (4) during data processing, all continuous variables were Winsorized at the 1% upper and lower limits. After these treatments, a final balanced panel dataset of 1022 enterprises with 9198 records from 2013 to 2021 was obtained.

2.2 Variable Definitions

2.2.1 Dependent Variable

Enterprise Risk-Taking. Higher risk-taking means that the enterprise faces increased uncertainty in future cash inflows. Previous studies have measured this using the volatility of enterprise earnings (i.e., the standard deviation; Chen and Milidonis, 2023). This study used the volatility of the enterprise's return on assets (*ROA*, calculated as *EBIT* divided by total assets at year-end) during the sample period to measure

the level of enterprise risk-taking. The *ROA* was adjusted by subtracting the industry average for each year to obtain *Adi_Roa*, which eliminated the effects of the economic cycle and industry factors. As risk-taking can be considered an active behavior of the enterprise, this study used three years (*t*, *t*+1, *t*+2) as an observation window. Here, we calculated the standard deviation and range (used for robustness checks) of the industry-adjusted *Adj_Roa* for each period. The specific calculation is shown in the following formula:

$$Adj_{Roa_{i,t}} = \frac{EBIT_{i,t}}{ASSET_{i,t}} - \frac{1}{X}\sum_{K=1}^{X}\frac{EBIT_{i,t}}{ASSET_{i,t}} \tag{1}$$

$$RiskT_{i,t} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{EBIT_{i,t}}{ASSET_{i,t}} - \frac{1}{X}\sum_{K=1}^{X}\frac{EBIT_{i,t}}{ASSET_{i,t}}\right)^{2} \mid T=3} \tag{2}$$

2.2.2 Explanatory Variables

Current indicators used to measure bank risk-taking include nonperforming loan ratio, Z-score, and the ratio of risk-weighted assets (Bitar *et al*., 2018). Among these, the nonperforming loan ratio reflects the quality of bank loans and represents passive risk-taking. The Z-score is commonly used to measure bankruptcy risk, but it does not reflect active risk-taking by banks. In comparison, the ratio of risk-weighted assets includes on-balance-sheet and off-balance-sheet risks, offering a more accurate reflection of the bank's overall risk-taking level. Therefore, the ratio of risk-weighted assets was used in this study to measure the bank's overall risk. Based on the loan relationship between enterprises and banks, and considering that the level of bank risk-taking itself can be inherently comprehensive, this study averaged the bank risk-taking at the enterprise level. The specific setup is as follows:

$$Bankrisk_{i,t} = \sum_{K=1}^{X}\frac{loan_{\text{int}}}{loan_{i,t}} \times Bankrisk_{nt} \tag{3}$$

The existing literature on the quantitative measurement of enterprise digital transformation primarily uses methods based on keyword analysis of annual reports. This study followed the measurement approach of the CSMAR database for assessing the level of digital transformation of listed companies. In particular, this study used the logarithm of the sum of the total frequency of relevant keywords, plus one, to represent the level of digital transformation in listed companies. Specifically, Python was used to extract keywords, such as "artificial intelligence," "blockchain," and "big data technology" from the Management Discussion and Analysis (MD&A) section of the annual reports of listed companies. The summed frequencies of these keywords were then log-transformed to create the enterprise digital transformation index (Ressi *et al*., 2024).

The core explanatory variable is the interaction term $Dcg_{it} = Post_t \times Treat_i$. If a sample bank and enterprise held a loan relationship, the sample was classified as the treatment group, with *Treat* assigned a value of 1. Otherwise, the sample was classified as the control group, with *Treat* assigned a value of 0. The variable *Post* indicates that the listed company has implemented digital transformation. The specific determination steps were as follows: First, we considered that some listed companies engaged in strategic

or selective disclosure of digital-related terms in their annual reports. If the digital transformation index, calculated by taking the log of the total frequency of relevant keywords for the sample period, was consistently greater than 0, we assumed that the company was more likely to disclose positive information. In this case, the probability of selective disclosure was higher, and the *Treat* value for the enterprise was set to missing. Thus, we excluded such samples.

Second, if there was a gap of 0 in the digital transformation index, this suggested significant resistance to digital transformation within the company. If the company's digital transformation index for all subsequent years was consistently greater than 0, we assumed that the company had a high likelihood of successfully transforming digitally. In this case, *Post* was assigned a value of 1, with all previous years assigned a value of 0. The coefficient of the interaction term reflects the impact of the digital transformation event on the change in risk-taking between banks and enterprises.

2.2.3 Control Variables

To ensure the accuracy and robustness of the research results, we controlled for the financial characteristics of banks and enterprises, as well as other relevant variables, to exclude the potential impact of different bank characteristics and enterprise financial features on changes in the bank–enterprise risk-taking relationship. At the bank level, the following variables were controlled: Bank Size (*Banksize*): The size of a bank directly affects its risk management and risk-taking ability. Larger banks typically have more resources, capital buffers, and risk diversification capabilities, allowing them to better cope with potential financial risks. As such, controlling for bank size helps eliminate the interference of scale effects on bank risk-taking, preventing the misjudgment of a positive relationship between larger bank size and higher risk-taking as being caused by digital transformation (Miao *et al*., 2025). Loan-to-Deposit Ratio (*Ldr*): The loan-to-deposit ratio reflects the proportion of loans to deposits at a particular point in time, indicating the bank's liquidity and risk tolerance. A higher loan-to-deposit ratio typically means a higher proportion of credit assets, exposing the bank to greater credit risk. Therefore, by controlling for this variable, we can avoid the influence of a bank's liquidity situation on its risk preferences in loan decisions (Kim, Sohn, 2024). Cost-to-Income Ratio (*Cer*): The cost-to-income ratio measures a bank's operational efficiency. A higher cost-to-income ratio may indicate that the bank faces greater cost pressures, which can affect its risk management strategy. As such, controlling for this variable helps identify whether a bank's cost management issues influence its support for enterprise credit and risk-taking (Baltas, 2025). Nonperforming Loan Ratio (*Banknol*): The nonperforming loan ratio reflects the proportion of loans with default risk. A higher nonperforming loan ratio means the bank faces greater credit risk, which, in turn, may lead it to adopt more conservative lending policies, reduce loan volumes, and tighten credit controls. Thus, by controlling for this variable, we can ensure that the impact of nonperforming loans does not negatively influence our research findings on bank risk-taking (Jiajia *et al*., 2023). Loan Loss Provision Ratio (*Lpr*): The loan loss provision ratio indicates the proportion of reserves a bank sets aside for potential bad debts. A higher provision ratio suggests that the bank has stronger risk-bearing capacity and can better handle bad debt risks. Therefore, it may be more lenient in its risk-taking behavior. For this reason, controlling for the loan loss provision ratio helps eliminate the impact of bank provisions, ensuring that credit decisions and risk-taking reflect changes brought about by digital transformation (Naiborhu, 2024).

Table 1. Variable Definitions

Variable Type	Variable Name	Variable Symbol	Calculation Method
Dependent Variable	Enterprise Risk-Taking Level	*Risk*	Three-year earnings volatility
Explanatory Variable	Bank Risk-Taking Level	*Bankrisk*	See previous text
	Bank Risk-Taking under Digital Shock	*Dcg*	See previous text
Control Variables	Bank Size	*Banksize*	*ln*(Bank's total assets + 1)
	Cost-to-Income Ratio	*Cer*	Operating cost / Operating income
	Nonperforming Loan Ratio	*Banknol*	Total nonperforming loans / Total loans
	Loan Loss Provision Ratio	*Lpr*	Loan loss provisions / Total loans
	Loan-to-Deposit Ratio	*Ldr*	Total loans / Total deposits
	Enterprise Size	*Size*	*ln*(Enterprise size + 1)
	Dual Role	*Dual*	Dual role = 1, Nondual role = 0
	Enterprise Growth	*Growth*	(Current revenue - Previous revenue) / Previous revenue
	Company Age	*FirmAge*	Current year - Enterprise establishment year
	Return on Assets	*ROA*	Net profit / Total assets
	Tobin's Q	*TobinQ*	Market value / Asset replacement cost
	Cash Flow Ratio	*Cashflow*	Cash flow from operating activities / Current liabilities
	Debt-to-Asset Ratio	*Lev*	Total liabilities / Total assets

Source: authors' own results.

Meanwhile, at the enterprise level, the following variables were controlled: Enterprise Size (*Size*): The size of an enterprise affects its risk-taking through its resource endowment, organizational structure, and management capabilities. Larger enterprises usually have more financial resources and technical support but may also face issues, such as lengthy decision-making processes and low innovation efficiency. Thus, controlling for enterprise size helps avoid the influence of scale effects on enterprise risk-taking, thus allowing for a more accurate analysis of how digital transformation impacts enterprise risk-taking (Dvorski, Miloš, 2024). Debt-to-Asset Ratio (*Lev*): The debt-to-asset ratio measures an enterprise's leverage in which a higher leverage ratio may lead to greater debt repayment pressure, suppressing the enterprise's risk-taking ability. As such, by controlling for the debt-to-asset ratio, we can differentiate between the effects of financial leverage and the independent impact of digital transformation on risk-taking (Kang and Baek, 2024). Return on Assets (*ROA*): The return on assets represents the profitability of an enterprise. High-profit enterprises typically have more internal funds to support risk-taking. However, high profitability may also lead to overconfidence among management, affecting their judgment of risk. Therefore, controlling for *ROA* helps analyze the potential endogenous effects of profitability on risk-taking (Jia and Zhang, 2024). Cash Flow Ratio (*Cashflow*): The cash flow ratio measures the relationship between an enterprise's liquid funds and liabilities, reflecting its debt-repayment ability and financial flexibility. Enterprises with abundant cash flow are more capable of assuming risk; hence, controlling for the cash flow ratio helps avoid interference from its financial status on risk-taking (Keefe, Nguyen, 2023). Revenue Growth Rate (*Growth*): The revenue growth rate reflects an enterprise's growth potential, and in particular, high-growth enterprises are generally more willing to take on risks to achieve high returns during expansion. In contrast, low-growth enterprises tend to be more conservative. Therefore, controlling for this variable helps prevent the misunderstanding of the relationship between enterprise growth and its risk-taking ability as being an effect of digital transformation (Kivilo *et al.*, 2025). Company Age (*FirmAge*): Company age reflects the stage of an enterprise's development. Younger enterprises are more likely to take risks to achieve rapid

growth, while mature enterprises tend to be more cautious and avoid excessive risks. Hence, controlling for company age helps exclude the influence of life-cycle stages on enterprise risk-taking (Yu *et al.*, 2024). Dual Role (*Dual*): Dual role refers to the scenario where the chairman and CEO are the same person. This can affect the efficiency of enterprise decision-making and risk-taking preferences. While a dual role may improve decision-making efficiency, it may also concentrate decision-making power, increasing management's risk-taking tendencies. Thus, controlling for this variable helps eliminate the independent influence of the management structure on enterprise risk-taking (Zhang and Liu, 2024). Tobin's Q (*TobinQ*): Tobin's Q reflects the ratio of a company's market value to the cost of replacing its assets. A higher Q value typically suggests that the enterprise has good market prospects and may be more willing to take on risks. Hence, controlling for Tobin's Q helps differentiate the impact of market value on enterprise risk-taking, preventing it from interfering with the research results (Nejadmalayeri and Usman, 2022). Specific variable explanations are shown in *Table 1*.

2.3 Descriptive Analysis

Table 2 presents the descriptive statistics for the main variables. As can be seen, the enterprise risk-taking level has a maximum value of 12.61 and a minimum value of 0.00123, indicating a significant variation in the risk-taking levels among the sample enterprises. The bank risk-taking level has a maximum value of 0.771, a minimum value of 0, and a standard deviation of 0.321. These results suggest that the weighted risk asset ratio for banks is still relatively high, indicating a large level of risk-taking. Moreover, there are clear differences in the risk-taking levels across different enterprises.

Table 2. Descriptive Statistics of the Sample

Variable	(1)	(2)	(3)	(4)	(5)
	N	Mean	Sd	Min	Max
Risk	9,198	0.455	1.346	0.00123	12.61
Dcg	9,198	0.675	0.469	0	1
Bankrisk	9,198	0.364	0.321	0	0.771
Banksize	9,198	17.03	14.69	0	31.14
Ldr	9,198	0.460	0.402	0	1.160
Lpr	9,198	0.0169	0.0149	0	0.0497
Cer	9,198	0.148	0.136	0	0.408
Banknol	9,198	0.821	0.734	0	2.390
Size	9,198	2.261	0.119	2.018	2.639
Growth	9,198	0.136	0.360	-0.657	3.224
Dual	9,198	0.220	0.414	0	1
Cashflow	9,198	0.0470	0.0633	-0.199	0.256
TobinQ	9,198	1.884	1.256	0	10.12
ROA	9,198	0.0351	0.0534	-0.269	0.219
FirmAge	9,198	2.958	0.313	1.792	3.555
Lev	9,198	0.456	0.196	0.00797	0.989

Source: authors' own results.

3. Results Analysis

3.1 Baseline Regression

This study constructed a two-way fixed-effects baseline regression model, shown in Equation (1), to examine the changes in the bank–enterprise risk-taking relationship. In this model, *Risk* is the dependent variable, representing the level of enterprise risk-taking, while *Bankrisk* is the explanatory variable,

representing the level of bank risk-taking. The coefficient γ_1 reflects the direction and magnitude of the impact of changes in bank risk-taking on enterprise risk-taking. Additionally, *X* represents a group of control variables; λ_i and δ_t represent the individual and time fixed effects, respectively; and μ_{it} is the random disturbance term.

$$Risk_{it} = \beta_1 + \gamma_1 Bankrisk_{it} + \varphi_1 X_{it} + \lambda_i + \delta_t + \mu_{it} \quad (4)$$

Table 3. The Relationship between Bank and Enterprise Risk-Taking

Variable	(1)	(2)	(3)
	Risk	***Risk***	***Risk***
Bankrisk	-0.659*** (-3.28)	-0.615*** (-5.68)	-0.551*** (-6.02)
Banksize	-0.692*** (-9.16)	-0.678*** (-8.79)	-0.667*** (-8.45)
Ldr	1.366*** (5.66)	0.782*** (6.07)	0.686*** (5.24)
Lpr	-2.166 (-0.57)	1.466 (0.42)	0.681 (0.19)
Cer	-0.887*** (-2.87)	-0.430 (-1.50)	-0.484 (-1.73)
Banknol	-0.199** (-2.34)	-0.115* (-1.79)	-0.062 (-1.07)
Size	-0.028 (-0.18)	1.933* (1.94)	1.942* (1.83)
Lev	-0.991*** (-11.02)	-0.695*** (-3.23)	-0.686** (-2.73)
ROA	-8.131*** (-27.18)	-5.599*** (-7.99)	-5.766*** (-8.24)
Cashflow	1.590*** (6.90)	0.749** (2.50)	0.847** (2.69)
FirmAge	0.125*** (2.79)	0.443** (2.37)	0.444 (1.45)
TobinQ	0.077*** (6.27)	-0.016 (-1.50)	0.014 (1.01)
Dual	0.167*** (5.10)	0.016 (0.38)	0.014 (0.33)
Growth	0.187*** (4.85)	-0.016 (-0.56)	-0.037 (-1.20)
Constant	0.558 (1.61)	-4.724** (-2.70)	-4.759* (-1.93)
Individual Fixed Effects	NO	YES	YES
Time Fixed Effects	NO	NO	YES
Observations	9,198	9,198	9,198
R-squared	0.097	0.075	0.081

Notes: The numbers in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Source: authors' own results.

Columns (1)–(3) present the baseline regression results for changes in risk-taking between banks and enterprises. In particular, Column (1) shows the mixed regression results for bank–enterprise risk-taking,

Column (2) shows the individual fixed effects regression results, and Column (3) shows the two-way fixed effects regression results. From Columns (1)–(3), we can see that the coefficient for bank risk-taking is significantly negative at the 1% level, indicating that before enterprises undergo digital transformation, the bank–enterprise risk-taking relationship shows a reverse trend.

This finding suggests that before digital transformation, the bank–enterprise risk-taking relationship essentially reflects a noncooperative game state in terms of information asymmetry, risk preferences, and resource allocation. Particularly when enterprises actively increase their risk-taking to seek development opportunities, the bank's risk aversion tendency becomes significantly stronger. As a result, the bank's credit behavior becomes more conservative, directly leading to a reduction in credit supply and an increase in financing thresholds, which in turn cause enterprises to face higher financing costs and reduced credit availability. Such actions, however, severely restrict their investment expansion, technological upgrades, and innovation capabilities.

This study constructed a two-way fixed-effects multiperiod DID model, shown in Equation (2), to examine the baseline effect of enterprise digital transformation on the bank–enterprise risk-taking relationship. In this model, *Risk* is the dependent variable, representing the level of enterprise risk-taking, and *Dcg* is the core explanatory variable, representing the development of bank risk-taking affected by enterprise digital transformation. The coefficient γ_2 reflects the direction and magnitude of the impact of digital transformation on the bank–enterprise risk-taking relationship. Additionally, *X* represents a group of control variables; λ_i and δ_t represent the individual and time fixed effects, respectively; and μ_{it} is the random disturbance term.

$$Risk_{it} = \beta_2 + \gamma_2 Dcg_{it} + \varphi_2 X_{it} + \lambda_i + \delta_t + \mu_{it} \quad (5)$$

Table 4. Baseline Effect of Enterprise Digital Transformation on the Bank–Enterprise Risk-Taking Relationship

Variable	(4)	(5)	(6)
	Risk	***Risk***	***Risk***
DCG	0.243** (2.11)	0.211*** (3.82)	0.162** (2.61)
Banksize	-0.037** (-2.36)	-0.028 (-1.46)	-0.026 (-1.02)
Ldr	0.005 (1.15)	-0.003 (-0.90)	-0.004 (-1.17)
Cer	-0.013* (-1.82)	0.008** (2.28)	0.007* (1.87)
Banknol	-0.199 (-0.99)	0.030 (0.16)	0.163 (1.12)
Lpr	0.060 (0.65)	-0.029 (-0.42)	-0.039 (-0.61)
Size	-0.047 (-1.43)	0.425*** (4.40)	0.445*** (3.75)
Lev	-0.657*** (-3.15)	-1.480 (-1.70)	-1.571 (-1.60)
ROA	-7.494*** (-11.52)	-5.804*** (-5.30)	-6.203*** (-5.23)
Cashflow	2.599*** (4.75)	1.854*** (3.16)	1.980*** (3.19)
Growth	0.255*** (3.43)	-0.085 (-1.17)	-0.095 (-1.33)

Table 4 (*continuation*). Baseline Effect of Enterprise Digital Transformation on the Bank–Enterprise Risk-Taking Relationship

Variable	(4)	(5)	(6)
	Risk	***Risk***	***Risk***
FirmAge	0.254** (2.33)	0.069 (0.35)	0.389 (0.38)
Dual	0.094 (1.21)	-0.169 (-1.25)	-0.185 (-1.41)
TobinQ	0.094*** (3.29)	-0.011 (-0.48)	0.023 (0.84)
Constant	0.940 (1.26)	-8.574*** (-4.32)	-9.848* (-2.19)
Individual Fixed Effects	NO	YES	YES
Time Fixed Effects	NO	NO	YES
Observations	1,926	1,926	1,926
R-squared	0.094	0.094	0.104

Notes: The numbers in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
Source: authors' own results.

Column (4) shows the mixed regression results after adding the impact of enterprise digital transformation, Column (5) shows the individual fixed-effects regression results with the impact of digital transformation, and Column (6) shows the two-way fixed-effects regression results after adding the impact of digital transformation. From Columns (4) to (6), we can see that after the inclusion of the digital transformation shock, the coefficients for the bank–enterprise risk-taking relationship are significantly positive, indicating that the relationship shows a synchronized trend after digital transformation. This result suggests that as digital transformation progresses, the noncooperative game relationship between banks and enterprises reverses, becoming more aligned in terms of risk-taking behavior. On the one hand, digital transformation improves enterprise transparency and data accessibility, which then alleviates information asymmetry between banks and enterprises, allowing banks to more accurately assess enterprise credit and risk, thereby increasing their willingness to lend. On the other hand, digital transformation reduces the financing constraints and marginal financing costs of enterprises, enhancing their risk-bearing capacity and financial flexibility. This enables enterprises to invest more in R&D, expand into new markets, and undertake strategic transformations, thereby stimulating their vitality.

3.2 Robustness Analysis

3.2.1 Parallel Trend Test

The validity of the multiperiod DID method relies on the parallel trends assumption. This means that before the digital transformation of some enterprises, the risk-taking levels in the sample should show a relatively consistent development trend to ensure that the effects captured by the differences are solely due to the gap caused by the digital transformation. *Table 5* presents the changes in the risk-taking levels between banks and enterprises before and after enterprise digital transformation. The dummy variables *d_i** and *di** represent the states at each time point before and after the enterprise digital transformation, respectively. The results reveal that the estimated coefficients of *d_i** are not significant, indicating that before digital transformation, the changes in the risk-taking behavior between banks and enterprises were consistent in the sample. This satisfies the parallel trends assumption.

Additionally, the estimated coefficients of *di** are significantly positive in the second and third periods after the transformation. The lack of significance in the first period after transformation may be due to the time lag of digital transformation, which does not immediately reflect in the changes in risk-taking behavior

between banks and enterprises. Meanwhile, the lack of significance in the fourth period after transformation may be influenced by the pandemic, which affected the survival and development of enterprises, leading to slower or stagnated digital transformation. Based on the above analysis, it can be concluded that after digital transformation, the overall increase in bank risk-taking is accompanied by an increase in enterprise risk-taking, both exhibiting a synchronized trend.

Table 5. Parallel Trend Test Results

risk	*Coefficient*	*Std. Err.*	*t-value*	*P>t*
d_4	-0.296	(0.172)	-1.72	0.139
d_3	-0.075	(0.114)	-0.66	0.797
d_2	-0.073	(0.090)	-1.24	0.242
d_1	-0.083	(0.081)	-1.25	0.239
d1	0.159	(0.165)	0.98	0.349
d2	0.266*	(0.128)	1.98	0.074
d3	0.302**	(0.089)	2.98	0.013
d4	0.157	(0.103)	0.73	0.479
Banksize	-0.578	(2.52)	-8.1	0.065
Ldr	0.010**	(-1.16)	-0.90	0.388
Cer	0.140	(3.02)	2.58	0.026
Banknol	-0.045	(0.76)	0.47	0.646
Lpr	-1.556	(-0.67)	-0.37	0.718
Size	-6.186***	(3.76)	3.55	0.005
Lev	1.957**	(-1.58)	-1.49	0.165
ROA	-0.092	(-5.13)	-2.9	0.014
Cashflow	0.352	(3.07)	3.39	0.006
Growth	-0.183	(-1.29)	-1.4	0.174
FirmAge	0.023	(0.36)	0.40	0.697
Dual	-0.005	(-1.41)	-0.87	0.403
TobinQ	0.010**	(2.52)	0.9	0.360
_cons	-10.041 **	(4.431)	-2.27	0.045

Notes: 1. The impact period was treated as the reference group, so “current” was excluded from the regression. 2. Numbers in parentheses represent standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Source: authors’ own results.

3.2.2 Placebo Test

To eliminate the interference of other policy shocks and unobservable omitted variables on the baseline regression results, and to further enhance the reliability of the research conclusions, this work conducted a placebo test by constructing a counterfactual model. The year of digital transformation for all enterprises was uniformly assumed to be 2017. The regression results are shown in *Table 6*. As can be seen, the estimated coefficient of *Dcg* is not significant in any of the models, which serves as a reverse confirmation of the baseline regression results in *Table 3*.

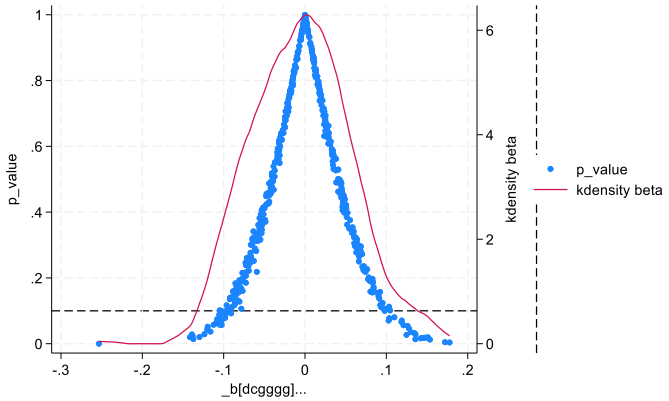
Table 6. Placebo Test 1: Assuming the Year of Enterprise Digital Transformation Impact to be 2017

Variable	(1)	(2)	(3)
	Risk	***Risk***	***Risk***
Dcg	0.172 (1.59)	0.068 (0.54)	0.009 (0.02)
Constant	1.442* (1.91)	-7.546** (-2.36)	-9.840* (-2.16)
Controls	YES	YES	YES
Individual Fixed Effects	NO	YES	YES
Time Fixed Effects	NO	NO	YES
Observations	1,926	1,926	1,926
R-squared	0.128	0.110	0.120

Notes: The numbers in parentheses represent standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Source: authors' own results.

Another common method for the placebo test is to randomly select the interaction term 500 times. In this study, the data were grouped by individual and year. For each individual, a random year was selected from the year variable as the policy period. After performing 500 random selections and regression tests, the p-value distribution was obtained, as shown in *Figure 1*. The results also reveal that most points in the DID constructed after random sampling are above the 10% significance level. This finding suggests that the significance of the random sampling is not significant, indicating that the regression results in *Table 4* are robust.



Source: authors' own results.

Figure 1. **Placebo Test 2: p-value Distribution**

3.2.3 Change in the Calculation Method of the Dependent Variable.

In this study, we changed the calculation method of the dependent variable *Risk*, adjusting it to (*t*-1, *t*, *t*+1). The regression results are shown in *Table 7*. As can be seen, the estimated coefficients of the variables *Bankrisk* and *Dcg* remain significantly negative. These results further support the conclusion that before digital transformation, an increase in bank risk-taking reduces the enterprise's risk-taking, reflecting an inverse relationship. After digital transformation, an increase in bank risk-taking leads to an increase in enterprise risk-taking, thus showing a positive relationship.

3.2.4 Core Explanatory Variable Lagged by One Period

Considering that digital transformation may have a lagged effect, we lagged the core explanatory variable by one period to further enhance the robustness of the empirical results. From Column (4) of *Table 7*, it can be observed that the coefficient of the interaction term is 0.167, which is significant at the 10% level. Therefore, the conclusion obtained is consistent with the baseline regression.

3.2.5 Exclusion of Special Samples

Due to missing loan records for some bank–enterprise pairs or zero loan amounts, the weighted core explanatory variables and some bank-level control variables were assigned a value of zero. After removing these samples and performing the regression again, the conclusions of this study remain valid.

Table 7. Robustness Check

Variables	(1)	(2)	(3)	(4)
	Risk	***Risk***	***Risk***	***Risk***
Bankrisk	-0.180*** (-3.28)			
Dcg		0.005** (2.41)	0.132* （2.17）	
L.Dcg				0.123* (2.12)
Constant	-0.464 (-0.43)	-0.067 (-0.58)	-0.502 (-0.47)	-0.078 (-0.62)
Controls	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES
Observations	9,198	1,926	396	1926
R-squared	0.017	0.069	0.188	0.101

Notes: The numbers in parentheses represent standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Source: authors' own results.

4. Further Analysis

4.1 Mechanism Analysis of the Impact of Enterprise Digital Transformation on the Change in Risk Taking between Banks and Enterprises

The conclusions above suggest that enterprise digital transformation changes the risk paradigm between banks and enterprises, shifting the risk sharing from an "inverse change" to a "parallel change." If so, why does the risk sharing between banks and enterprises undergo a fundamental shift due to enterprise digital transformation? To uncover this underlying logic, we focused on two perspectives: information asymmetry and financing constraints. In particular, we investigated the mechanisms by which enterprise digital transformation reshapes the risk-taking relationship between banks and enterprises.

4.1.1 Information Asymmetry Mechanism

In this work, we used the sum of the absolute values of a firm's discretionary accruals over the past three years (*Opaque*) to measure its information asymmetry (Battigalli *et al*., 2024).

$$Opaque = Abs(DisAcc_{i-1}) + Abs(DisAcc_{i-2}) + Abs(DisAcc_{i-3}) \quad (6)$$

The discretionary accruals (*DisAcc*) were estimated using the modified Jones model (Hao *et al*., 2020). Specifically, we conducted annual and industry-specific regressions using the model. The estimated regression coefficients were then substituted into the equation to estimate the discretionary accruals, *DisAcc*.

$$\frac{TA_{i,t}}{Asset_{i,i-1}} = \alpha_1 \frac{1}{Asset_{i,i-1}} + \alpha_2 \frac{\Delta REV_{i,t}}{Asset_{i,i-1}} + \alpha_3 \frac{\Delta PPE_{i,t}}{Asset_{i,i-1}} + \varepsilon_{i,t} \tag{7}$$

$$DisAcc_{i,t} = \frac{TA_{i,t}}{Asset_{i,i-1}} - (\hat{\alpha}_1 \frac{1}{Asset_{i,i-1}} + \hat{\alpha}_2 \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{Asset_{i,i-1}} + \hat{\alpha}_3 \frac{\Delta PPE_{i,t}}{Asset_{i,i-1}}) \tag{8}$$

In accordance with the formula in the model design, the regressions were conducted sequentially to test the mechanisms, with the results shown in *Table 8*. Regressions (1)–(3) tested the mediating effect of the absolute sum of discretionary accruals (Opaque) over the past three years. In regression (2), the regression coefficient for *Dcg* is -0.014, which is significant at the 10% level. In regression (3), the estimated coefficient for Opaque is significantly negative, while the estimated coefficient for *Dcg* is significantly positive. This indicates that Opaque acts as an incomplete mediating variable in the process of change in the risk-sharing relationship between banks and enterprises due to digital transformation. The path of "enterprise digital transformation—enterprise information asymmetry—bank–enterprise risk-sharing" is valid. This shows that digital transformation can reduce information asymmetry within enterprises, thereby promoting the synchronous change in risk-sharing between banks and enterprises.

4.1.2 Financing Constraint Mechanism

Next, we used the *SA* index to measure the level of financing constraints faced by enterprises, where the higher the value, the more severe the financing constraints for the enterprise.

$$SA_{i,t} = -0.737 \times SIZE_{i,t} \pm 0.043 \times SIZE_{i,t}^2 - 0.04 \times AGE_{i,t} \tag{9}$$

Based on the formulas in the model design, regression tests were conducted step by step to examine the mechanism, with the results shown in *Table 8*. Regressions (1), (4), and (5) tested the mediating effect of enterprise financing constraints, represented by SA. In regression (4), the coefficient of *Dcg* is -0.090, which is significant at the 1% level. In regression (5), the estimated coefficients of SA and *Dcg* are significantly negative and positive, respectively. It can be seen that SA acts as an incomplete mediator in the process of how digital transformation influences the changes in risk-taking between banks and enterprises. This finding indicates that the "digital transformation - enterprise financing constraints - bank–enterprise risk-taking" transmission pathway is effective. It also shows that digital transformation can reduce financing constraints for enterprises, thus promoting the alignment of bank–enterprise risk-taking.

Table 8. Mechanism Analysis

Variable	Baseline Regression	Mediator			
	Risk	***Opaque***	***Risk***	***SA***	***Risk***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Opaque			-0.035** (-2.89)		
SA					-1.878*** (-4.40)
Dcg	0.162** (2.61)	-0.016* (-1.97)	0.005* (1.94)	-0.095*** (-9.75)	0.196** (2.63)
Constant	-10.300** (-2.23)	-0.844** (-2.61)	-0.107 (-0.85)	-0.759** (-2.14)	-0.098 (-0.91)
Controls	*YES*	*YES*	*YES*	*YES*	*YES*
Individual Fixed Effects	*YES*	*YES*	*YES*	*YES*	*YES*
Time Fixed Effects	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	1,926	1,926	1,926	1,926	1,926
R-squared	0.109	0.035	0.097	0.085	0.086

Notes: The values in parentheses represent standard errors. *, ** and *** denote significance levels at 10%, 5%, and 1%, respectively.

Source: authors' own results.

4.2 Impact of Enterprise Competition Level on Changes in Risk Taking between Banks and Enterprises after Digital Transformation

To examine the impact of enterprise competition level on changes in risk bearing between banks and enterprises after digital transformation, we constructed an interaction term between *Dcg* and the level of enterprise competition for empirical testing. The enterprise competition intensity measure, the Lerner index, was sourced from the CSMAR database. A higher Lerner index indicates greater monopoly power of an enterprise, whereas a lower index reflects stronger competition within the enterprise.

Table 9. Analysis of the Impact of Enterprise Competition Level

Variable	Benchmark Regression	Moderating	
	Risk	***Risk***	***Risk***
	(1)	**(2)**	**(3)**
Lerner		-0.342 (-0.27)	-0.135 (-0.15)
Dcg	0.162** (2.61)	0.144** (2.36)	0.230** (2.49)
*Lerner*Dcg*			-0.759* (-1.91)
Constant	-10.300** (-2.23)	-10.443** (-2.45)	-10.662** (-2.50)
Controls	*YES*	*YES*	*YES*
Individual Fixed Effects	*YES*	*YES*	*YES*
Time Fixed Effects	*YES*	*YES*	*YES*
Observations	1,926	1,926	1,926
R-squared	0.109	0.110	0.112

Notes: The numbers in parentheses represent the standard errors. The asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Source: authors' own results.

Based on the benchmark regression, we introduced the level of enterprise competition, Lerner, and reported the corresponding results in *Table 9*. It can be observed that the interaction term between the level of enterprise competition and the core explanatory variable, *Dcg*, has a coefficient of -0.756, which is statistically significant at the 10% level. This finding indicates that the level of enterprise competition moderates the impact of digital transformation on changes in risk-bearing between banks and enterprises. Specifically, the greater the degree of monopoly in an enterprise, the less intense the competition, which then leads to a slower change in risk-bearing between banks and enterprises under the impact of digital transformation.

4.3 Heterogeneity Analysis

4.3.1 Heterogeneity Analysis Based on the Perspective of Enterprise Digital Transformation

Differences in the level of enterprise digital transformation may lead to varying changes in risk-taking between banks and enterprises. This study classified the keywords "artificial intelligence," "blockchain," and "big data technologies" from corporate annual reports. These digital transformation keywords were further subdivided into two dimensions: underlying technologies and digital applications. To facilitate inter-group comparison, we divided the enterprises into four groups based on the median number of keywords: high and low levels of underlying technologies and high and low levels of digital applications. Next, we examined the changes in risk-taking behavior between banks and enterprises within each group.

From *Table 10*, it can be observed that for enterprises with low development of underlying technologies, the coefficient of the core explanatory variable *Dcg* is negative and not significant. In contrast, for enterprises with higher levels of underlying technology, the coefficient of *Dcg* is positive and significant. This finding may be due to the fact that enterprises with higher levels of digital transformation have a more complete technological foundation, such as AI, blockchain, and big data analysis. These enterprises are often able to provide higher-quality and more structured operational and financial data, which reduces the uncertainty in the bank's credit evaluation. As a result, it enhances the bank's willingness to support the enterprise's risk-taking, thus leading to a synchronized increase in risk-taking between banks and enterprises.

Table 10. Heterogeneity Analysis Based on the Perspective of Enterprise Digital Transformation

Variable	Underlying Technology		Digital Application	
	Low Underlying Tech	High Underlying Tech	Low Level of Digital Application	High Level of Digital Application
	Risk	*Risk*	*Risk*	*Risk*
Dcg	-1.541 (-1.46)	4.480* (2.36)	0.221 (1.33)	0.584 (1.62)
Constant	3.110 (0.52)	-32.905 (-1.30)	-12.139 (-1.25)	2.306 (0.32)
Controls	*YES*	*YES*	*YES*	*YES*
Individual Fixed Effects	*YES*	*YES*	*YES*	*YES*
Time Fixed Effects	*YES*	*YES*	*YES*	*YES*
R-squared	0.169	0.921	0.112	0.157

Notes: The numbers in parentheses represent standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Source: authors' own results.

In contrast, enterprises with weaker underlying technological capabilities due to their insufficient abilities in information processing, risk management, and technology integration are unable to fully demonstrate their operational stability or technological growth potential to banks. This scenario leads to an insignificant result in the risk-taking behavior between banks and enterprises. On the digital application front, while enterprises attempt to optimize operational efficiency through marketing digitalization, customer service digitalization, and other means, these surface-level applications mostly focus on auxiliary systems and have not yet directly impacted the core business and asset structure of the enterprise. As such, they are unable to significantly improve the enterprise's financing capacity or risk absorption ability, resulting in their failure to effectively signal the enhancement of the enterprise's value. Thus, in empirical terms, while the coefficient is positive, it is not significant.

4.3.2 Heterogeneity Analysis Based on Corporate R&D Investment Perspective

As an important source of funding for enterprises, different levels of R&D investment lead to varying funding needs, which in turn, affect the changes in the risk-taking relationship between banks and enterprises. Therefore, we used "R&D expenditure as a percentage of total assets at the beginning of the period" to measure the intensity of a company's R&D investment. In particular, this indicator reflects the company's strategic intentions and resource allocation levels in technological innovation and digital transformation (Šimáková and Pražák, 2023). To effectively avoid the impact of extreme values, we divided the sample into two groups: high and low R&D investment groups based on the median amount of R&D investment for the year, and performed separate regressions.

Table 11. Heterogeneity Analysis Based on Corporate R&D Investment Perspective

Variable	High R&D Investment	Low R&D Investment
	Risk	***Risk***
Dcg	4.480* (2.36)	-1.541 (-1.46)
Constant	-32.905 (-1.30)	3.110 (0.52)
Controls	*YES*	*YES*
Individual Fixed Effects	*YES*	*YES*
Time Fixed Effects	*YES*	*YES*
R-squared	0.921	0.169

Notes: The values in parentheses represent standard errors. * ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Source: authors' own results.

The results, shown in *Table 11*, indicate that for companies with higher R&D investment, the estimated coefficient of *Dcg* is significantly positive. In contrast, for companies with lower R&D investment, the estimated coefficient of *Dcg* is negative and not significant. This finding suggests that companies with higher R&D investment focus more on data integration and information disclosure. Furthermore, these companies have stronger technological innovation capabilities and higher growth potential. When banks assess their future debt repayment ability and investment returns, they are more likely to form positive expectations, thus increasing their willingness to extend credit. This, in turn, leads to a coordinated increase in risk-taking between the bank and the enterprise, further strengthening their cooperative relationship. Conversely, companies with lower R&D investment have weaker innovation capabilities and unclear future profit expectations, resulting in insignificant regression outcomes. Therefore, the level of R&D investment not only reflects the depth and quality of a company's digital capabilities but also

substantially impacts the bank's risk assessment mechanisms and credit allocation behaviors. Moreover, the level of R&D investment is an important factor that differentiates changes in the bank–enterprise risk-taking relationship. The above heterogeneity results also suggest that promoting increased R&D investment by enterprises is one of the key paths to achieving collaborative development between banks and enterprises.

4.3.3 Heterogeneity Analysis Based on Corporate Information Transparency

The level of information transparency in a company can lead to significant differences in credit allocation effects. In particular, high levels of information asymmetry increase a company's search and information costs, resulting in higher transaction costs (Choi and Han, 2023). Therefore, we used the sum of the absolute values of the discretionary accruals over the past three years (*Opaque*) to measure information transparency in an enterprise (Battigalli *et al*., 2024), where the higher the *Opaque*, the lower the firm's information transparency. To improve the feasibility and robustness of the comparison, the sample was divided into two groups based on the median of the company's information transparency for the year: high and low transparency groups, with regressions conducted for each.

The results, shown in *Table 12*, indicate that in the high transparency group, the coefficient of the core explanatory variable *Dcg* is 0.126 and significantly positive. In the low transparency group, *Dcg* is positive but not significant. This finding suggests that when a company has higher information transparency, the impact of its digital transformation on the synchronous change in risk-bearing between the bank and the enterprise is more pronounced. This result may be because companies with higher transparency can more effectively disclose their operational status, financial condition, and strategic changes during digital transformation. As such, their true intentions and progress are more easily understood and captured by the market and financial institutions, creating stronger positive market signaling effects. This, in turn, significantly reduces information asymmetry between the bank and the enterprise, increases the company's credibility in the credit market, and enables banks to more accurately assess the company's risk status and future development potential. Consequently, banks are more willing to increase their risk-bearing levels and share development risks with the enterprise. In contrast, for enterprises with lower information transparency, banks find it difficult to accurately assess the true effects and sustainability of the company's digital transformation due to the lack of effective disclosure of financial information and business progress. This, in turn, leads to more conservative risk assessments, thereby limiting the occurrence of synchronous changes in risk-bearing between the bank and the enterprise.

Table 12. Heterogeneity Analysis Based on Corporate Information Transparency

Variable	High Information Transparency	Low Information Transparency
	Risk	***Risk***
Dcg	0.135** (3.42)	0.057 (0.45)
Constant	-15.689** (-2.64)	-6.842 (-1.09)
Control Variables	*YES*	*YES*
Individual Fixed Effects	*YES*	*YES*
Time Fixed Effects	*YES*	*YES*
R-squared	0.142	0.151

Notes: Values in parentheses are standard errors. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Source: authors' own results.

5. Discussion

This study aimed to address several research questions. First, does digital transformation necessarily enhance the level of risk collaboration between enterprises and banks? Existing research generally suggests that digital transformation can improve corporate efficiency, enhance the financing environment, and reduce information asymmetry, thus promoting collaboration between enterprises and banks (Liu and He, 2024). Based on information asymmetry and financing constraint theories, it seems possible to infer that digital transformation should strengthen the risk-sharing mechanism between enterprises and banks by improving information transparency and financing availability (Li and Wang, 2023).

Theoretically, the higher the level of digital transformation in an enterprise, the more accurately banks can obtain business data, cash flow stability, and debt-bearing capacity; thus, their risk support should become more proactive (He *et al*., 2025). However, based on the empirical findings from Chinese A-share listed companies, the present study suggests that in the context of emerging markets, information asymmetry and financing constraint theories offer new explanatory pathways. The expected effects of digital transformation are not unconditional. In accordance with information asymmetry theory, digital transformation enhances the transparency of enterprise operations but also exposes more strategic information in data disclosures, including business models, market expansion pace, and even research and development progress (Chai *et al*., 2025). Furthermore, excessive transparency might weaken the competitive advantage of enterprises based on technological barriers, especially in highly competitive industries, where this information leakage could, in turn, discourage enterprises from taking on high-risk projects (Alex, 2025). Meanwhile, from the perspective of financing constraints, although digital transformation improves the ability of banks to assess risks, enterprises often face significant capital-intensive investment needs and increased profit volatility during the early stages of digital transformation. This, in turn, can lead to banks adopting a "defensive credit policy," which involves increasing capital requirements and strengthening credit constraints to prevent potential losses (Shahhosseini, 2022).

Unlike traditional literature that emphasizes "digital transformation easing financing pressure," this study's mechanism analysis shows that while digital transformation enhances financing accessibility, it also objectively amplifies banks' perception of enterprise risks, resulting in volatility in risk-taking rather than a linear improvement. The findings further suggest that because digital transformation affects accelerated information transparency and amplified risk exposure, the mechanism analysis follows an "increased enterprise risk-taking - improved bank risk collaboration" pattern. However, this is contingent on enterprises having strong technical foundations and high-quality information. Otherwise, this information disclosure could trigger banks' risk control mechanisms prematurely. Therefore, the verification of H1 and H2 also indicates that the positive impact of digital transformation on bank–enterprise collaboration is conditional and phase-dependent.

Second, is the positive effect of digital transformation on the enterprise-bank risk relationship controllable? Can the effect be amplified through strategic optimization? The heterogeneity analysis in this study suggests that the promoting effect of digital transformation on the bank–enterprise risk collaboration is significantly conditional and does not automatically manifest in all enterprises. Specifically, for enterprises with high digital transformation levels, strong R&D investment, and good information transparency, their risk-taking relationships with banks are more likely to show a synchronized change. In contrast, for enterprises with weak digital foundations, insufficient R&D investment, or lower information transparency, their risk-taking relationships with banks may still maintain a reversed relationship or even become further misaligned.

Furthermore, the moderation effect analysis reveals that the level of competition in an industry plays either a key "amplifying" or "diminishing" role in the effect of digital transformation; that is, the more intense the competition, the stronger the promoting effect of digital transformation on risk sharing between enterprises and banks. However, in less competitive, more monopolistic industries, the positive impact of digital transformation is compressed. This finding suggests that digital transformation does not act in isolation, but is embedded within an institutional context formed by the competitive environment and technological conditions of the enterprise. Therefore, it is highly "adjustable" and "malleable" (Wang *et al*., 2025).

At the enterprise level, enterprises with strong underlying technological capabilities have higher data integration, algorithm processing, and real-time disclosure abilities. They can effectively convert a large amount of operational data into risk information that banks can recognize and verify. This, in turn, enhances the support of digital construction for credit evaluation and loan matching, thus building a "data-driven risk-sharing mechanism" (Burzoni *et al*., 2024). High R&D investment enterprises also release long-term growth signals through continuous innovation, making it easier for banks to interpret the profit fluctuations brought about by digital transformation as "strategic investments" rather than "operational deterioration." As a result, this reduces the conservative bias against high-risk projects (Yang and Song, 2024).

In industries with high competition, the value of these positive signals is further amplified. Due to fierce industry competition and greater profit fluctuations, banks place higher reliance on real-time, high-quality data. Therefore, they benefit more from digitalization, willing to simultaneously increase their risk tolerance and achieve stronger risk collaboration with enterprises. Conversely, in industries with higher monopoly levels and insufficient competition, where external constraints on enterprises are weaker and profitability stability is high, the additional information has limited marginal explanatory power for banks' credit behavior, even if digital transformation is implemented. Hence, it becomes difficult to significantly improve the direction of the risk-sharing relationship between enterprises and banks.

From the perspective of financial institutions and regulators, the abovementioned results indicate that the effects of digital transformation are significantly controllable and have room for improvement. Banks can build differentiated data-driven credit models and dynamic risk tolerance mechanisms based on industry competition characteristics and the technological foundation of enterprises. This strategy would help avoid excessive credit contraction due to short-term performance fluctuations in the early stages of digitalization, especially in highly competitive industries in which proactive use of digital information to reduce noise risks should be emphasized to support high-quality enterprises.

Meanwhile, to prevent industry competition pressure from squeezing the positive effects of digitalization, regulators should provide greater policy support for enterprises actively engaging in digital construction in highly competitive industries, while maintaining the risk bottom line. In conclusion, the positive effect of enterprise digital transformation can be strengthened not only through improvements in the enterprise's own technology and governance capabilities but also effectively amplified by adjusting the industry competition environment and financial institutions' risk preferences.

Conclusions and Implications

Conclusions

This study systematically examined the impact of enterprise digital transformation on the change in the bank–enterprise risk-sharing relationship, based on data from A-share listed non-financial companies

from 2013 to 2023. A DID method with multiple time points was applied, further identifying its mechanisms of action and heterogeneity effects. The main conclusions are as follows:

(1) The digital transformation of enterprises significantly alters the direction of the bank–enterprise risk-sharing relationship. Before the implementation of digital transformation, the risk-sharing relationship between the two parties showed an inverse trend. That is, when the enterprise's risk-taking level increased, the bank's risk-taking decreased, further intensifying the enterprise's financing constraints. However, after the digital transformation, the risk-sharing relationship shifts to a positive trend, indicating that the bank will also increase its risk exposure when the enterprise's risk-taking increases, significantly enhancing risk-sharing and credit support.

(2) The alleviation of information asymmetry and the improvement of financing constraints are key mechanisms that drive the transformation from "inverse movement" to "positive movement" in the bank–enterprise risk-sharing relationship. In particular, digital transformation enhances operational information transparency and data accessibility, effectively reducing the information gap between banks and enterprises and mitigating adverse selection and moral hazard. At the same time, it expands financing channels, improves capital allocation efficiency, and strengthens the financial flexibility of enterprises, thus promoting the formation of a dynamic link between banks and enterprises in risk-adjusted returns, resulting in "risk-return synergy."

(3) The degree of competition significantly strengthens the change in the bank–enterprise risk-sharing relationship driven by digital transformation. In more competitive industries, digital transformation is more likely to enhance the shift in the risk-sharing relationship from "inverse movement" to "positive movement." However, in industries with higher levels of monopoly and insufficient competition, this effect is notably weakened. The stronger the competition, the higher the operational uncertainty, and banks become more reliant on real-time, verifiable digital information. Consequently, they are more likely to expand their risk exposure when enterprises increase their risk-taking, achieving risk collaboration. At the same time, in industries with insufficient competition, banks rely more on relational information, and the incremental value brought by digitalization is limited.

(4) The effects of digital transformation exhibit significant heterogeneity across different types of enterprises. On the one hand, enterprises with strong foundational digital capabilities, higher R&D investments, and better information transparency show a more pronounced positive shift in the risk-sharing relationship between banks and enterprises. On the other hand, for enterprises with weak foundational capabilities or insufficient data governance, the effects of digital transformation are either not significant or may even be negative. This finding indicates that the positive effects are controllable and offer potential for optimization, thus providing important guidance for enterprises in selecting digital strategies.

Policy Implications

The conclusions of this study offer the following policy implications:

(1) Enterprise digital transformation must be elevated as a core strategy to enhance risk governance and the financing environment. Regulatory bodies and enterprises should work together to elevate digital transformation from an "efficiency tool" to a "risk-financing integrated governance" strategic initiative. At the policy level, measures such as tax incentives, special subsidies, and pilot programs can guide enterprises in developing clear digital transformation roadmaps and organizational structures. Furthermore, such an approach should balance multiple goals, including operational efficiency, risk

management, and alleviating financing constraints, to prevent the formalistic tendency of "transforming for the sake of transformation."

(2) The bank–enterprise collaboration mechanism must be optimized, and the data-driven credit allocation and risk-sharing must be strengthened. On the one hand, it is important to further improve the enterprise information disclosure and data-sharing system. Doing so will promote the standardization and verifiability of financial, operational, and supply chain data, providing a reliable foundation for banks to conduct refined risk control and reasonable pricing. On the other hand, banks should be encouraged to deeply utilize digital technologies, such as big data and cloud computing, to innovate credit models. These also include supply chain finance, data asset pledges, online credit loans, etc. Under the premise of controllable risks, these measures can enhance credit support for digital enterprises, shifting from a "collateral-driven" to a "data-driven" risk-sharing model.

(3) Flexible competition and regulatory policies must be enforced to fully leverage the amplifying effect of competition on digitalization. For industries with intense competition, differentiated capital constraints, counter-cyclical adjustment tools, and transparent data supervision can be used while maintaining the bottom line of systemic risk. With the support of digital risk control, these measures will encourage banks to moderately increase their risk tolerance and credit allocation, fostering stronger alignment between banks and enterprises within the "risk-revenue sharing" framework. In industries with high monopoly levels and insufficient competition, measures such as implementing antimonopoly enforcement, breaking implicit guarantees and soft budget constraints, and strengthening mandatory information disclosure should be implemented. These actions will weaken the substitutive effect of relationship-based credit on digital information and guide digital transformation to truly become an endogenous driving force for optimizing credit resource allocation and enhancing bank–enterprise risk coordination.

(4) A layered and categorized digitalization and risk management policy combination must be implemented based on enterprise heterogeneity. Given the degree of digitalization, R&D investment, and information transparency can significantly affect the intensity of risk-sharing alignment between banks and enterprises, it is recommended to implement refined policy arrangements based on enterprise characteristics. In particular, for enterprises with a solid digital foundation, high R&D intensity, and good information transparency, greater support should be provided in credit access, credit limits, and innovation of financing tools. For enterprises with weak digital capabilities or low information transparency, the focus should be on guiding technological upgrades, governance improvements, and standardized information disclosure. These steps will gradually enhance their digital and risk management capabilities to achieve innovation incentives and financing support under the premise of controllable risks.

Limitations and Future Directions

This study has certain limitations. First, the sample range and identification strategy still have room for improvement. In particular, we used A-share listed non-financial companies from 2013 to 2023 and their credit relationships with commercial banks as the sample. While it provides a clear picture of typical bank–enterprise risk interactions, it has limited focus on unlisted small and medium-sized enterprises (SMEs), nonbank financial institutions, and diversified financing channels, such as supply chain finance. Therefore, the generalization of the findings to a broader range of entities requires further verification. Furthermore, while the multiperiod DID method alleviates endogeneity issues to some extent, the timing and intensity of enterprises' digital transformation may still be influenced by various factors, such as management preferences, local policies, and industrial clustering. Thus, future research could combine policy pilots or regional digital infrastructure development to create richer quasi-natural experiments and moderately

expand the sample range. This step would help improve the robustness and universality of the findings from different dimensions.

Second, the measurement of key variables and identification of mechanisms still leave room for further refinement. This study measured digital transformation based on annual report keywords, characterized bank–enterprise risk-taking using ROA volatility and risk-weighted assets, and represented information asymmetry and financing constraints through discretionary accruals and the SA index. These methods are feasible under the current data conditions but are still composite indicators, making it difficult to distinguish between different types of digital investment and various risk structures. In future research, richer data could be incorporated, such as bank–enterprise loan contract-level data and transaction and supply chain network data, along with methods like text mining. Doing so would help construct more advanced digital quality and risk structure indicators, and use mediation effect decomposition or network analysis tools to more precisely identify the micromechanisms through which enterprise digital transformation reshapes bank–enterprise risk-taking relationships.

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KAIP SKAITMENINĖ ĮMONIŲ TRANSFORMACIJA KEIČIA RIZIKOS PASIDALIJIMĄ TARP BANKŲ IR ĮMONIŲ: DAUGIAPERIODŽIO DID ANALIZĖS VERTINIMAS

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Santrauka. Įmonių skaitmeninė transformacija laikoma pagrindiniu kintamuoju, keičiančiu bankų ir įmonių santykius ir didinančiu finansų sistemos atsparumą. Tačiau literatūroje retai pateikiamas sistemingas aiškinamasis pagrindas ar teoriniai mechanizmai, kaip tai keičia bankų ir įmonių rizikos prisiėmimo elgseną. Remiantis informacijos asimetrijos ir finansavimo apribojimų teorijomis, pasitelkus ne finansų biržoje kotiruojamų bendrovių duomenis Kinijos A akcijų rinkoje nuo 2013 iki 2021 m., pritaikytas daugiaperiodis skirtumų modelis. Siekta ištirti, kaip įmonių rizikos prisiėmimas veikia bankų rizikos prisiėmimą. Nevienalytis poveikis buvo ištirtas remiantis įmonių skaitmeninės transformacijos lygiu, investicijomis į MTEP ir informacijos skaidrumu. Rezultatai atskleidė, kad įmonių rizikos prisiėmimas reikšmingai slopina bankų rizikos prisiėmimą, rodo aiškų atvirkštinį pokytį. Be to, rezultatai, įtraukus skaitmeninės transformacijos poveikį, rodo, kad įmonių rizikos prisiėmimas reikšmingai skatina bankų rizikos prisiėmimą, o tai lemia aiškų teigiamą pokytį. Įmonių rizikos prisiėmimas taip pat skatina bankų rizikos prisiėmimą per informacijos asimetrijos ir finansavimo apribojimų mechanizmus, kurie veikia tarpininkaujančiai. Įmonių konkurencijos laipsnis teigiamai moderuoja tarp įmonių ir bankų rizikos prisiėmimo, taip sustiprindamas įmonių rizikos prisiėmimo skatinamąjį poveikį bankų rizikos prisiėmimui. Be to, įmonių rizikos prisiėmimo įtaka bankų rizikos prisiėmimui yra nevienalytė. Įmonės, pasižyminčios aukštesniu skaitmeninės transformacijos lygiu, didesnėmis investicijomis į mokslinius tyrimus ir plėtra bei aukštesniu informacijos skaidrumu, yra labiau teigiamai skatinančios. Išvados suteikia sprendimų priėmimo pagrindą koordinuotai skatinti bankų ir įmonių rizikos pasidalijimą taikant skaitmeninę transformaciją.

Reikšminiai žodžiai: įmonės skaitmeninė transformacija; banko rizikos prisiėmimas; įmonės rizikos prisiėmimas; daugiaperiodis DID; bankų ir įmonių rizikos pasidalijimo pokyčiai.