The Removal of Implicit Guarantees and the Correction of Risk Pricing: Micro-level Evidence from the "New Asset Management Regulations"

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Abstract

For a long time, some state-owned enterprises (SOEs) have maintained high credit ratings and low-cost financing by relying on implicit guarantees and expectations of rigid redemption. This has not only severely distorted the market's risk pricing mechanism but also fostered phenomena such as "capital idling" and "financial arbitrage" among real-economy enterprises, exacerbating the government's debt risks and burdens. Taking the introduction of the "New Asset Management Regulations" in 2018 as a quasi-natural experiment, this paper constructs a triple-difference (DDD) model based on data from A-share listed companies to empirically examine the actual impact of this policy on the implicit guarantee premiums of high-rated SOEs and its micro-mechanisms.

The study finds that: (1) The New Asset Management Regulations have a significant stripping effect on the implicit guarantee premiums of high-rated SOEs, and this corrective effect is primarily concentrated in SOEs with larger asset scales; (2) The release of the policy effect follows a gradual path, initially appearing upon implementation in 2018 and reaching its peak after a series of substantive default events of high-rated SOEs occurred in 2020; (3) Even in a macroeconomic environment characterized by the superposition of loose monetary policy and market risk aversion, the pricing correction at the micro level still demonstrates strong resilience. Further mechanism analysis reveals a "scissors gap" phenomenon between the comprehensive financial burden and explicit borrowing costs, indicating that while correcting explicit risk pricing, the New Asset Management Regulations also play a clear and substantive role in rectifying the balance sheet structures of SOEs that over-rely on financial arbitrage and implicit credit support.

Keywords: New Asset Management Regulations; State-owned Enterprises; Implicit Guarantee; Rigid Redemption; Risk Pricing

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Full Text

Preamble

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摘要

For a long time, some state-owned enterprises (SOEs) have relied on implicit guarantees and expectations of rigid redemption to maintain high credit ratings and low-cost financing. This has not only severely distorted market risk pricing mechanisms but has also fostered phenomena such as "capital idling" and "financial arbitrage" among real-sector enterprises, thereby increasing the government's debt risk and fiscal burden. Using the introduction of the 2018 "New Asset Management Regulations" as a quasi-natural experiment, this paper constructs a triple-difference (DDD) model based on data from A-share listed companies to empirically examine the actual impact of this policy on the implicit guarantee premiums of high-rated SOEs and its underlying micro-mechanisms.

The study finds that: (1) the New Asset Management Regulations have a significant stripping effect on the implicit guarantee premiums of high-rated SOEs, and this corrective effect is primarily concentrated in SOEs with larger asset scales; (2) the release of the policy effect follows a gradual path, initially appearing upon implementation in 2018 and reaching its peak in 2020 following a series of substantive default events by high-rated SOEs; (3) even in a macroeconomic environment characterized by the convergence of loose monetary policy and market risk aversion, the micro-level pricing correction demonstrates strong resilience. Further mechanism analysis reveals a "scissors gap" phenomenon between the comprehensive financial burden and explicit borrowing costs. This suggests that while the New Asset Management Regulations correct explicit risk pricing, they also exert a significant substantive corrective effect on the balance sheet structures of SOEs that are overly dependent on financial arbitrage and implicit credit support.

关键词

Correcting Risk Pricing Bias: The Impact of the New Asset Management Regulations on the Pricing of Implicit Guarantees

Abstract

The implementation of the "New Asset Management Regulations" (New Regulations) represents a critical milestone in China' s financial structural reform, specifically targeting the long-standing issue of "rigid redemption" (gangxing duifu) and the resulting distortion in risk pricing. This study investigates whether the New Regulations have effectively corrected risk pricing bias by dismantling implicit guarantees. Utilizing a Triple-Difference (DDD) model, we analyze the yield spreads of corporate bonds to assess the policy' s impact on market-based risk assessment. Our findings suggest that the New Regulations have significantly increased the credit spreads of bonds previously benefiting from strong implicit guarantees, particularly those issued by State-Owned Enterprises (SOEs) and Local Government Financing Vehicles (LGFVs). This indicates a shift toward a more market-oriented risk pricing mechanism where credit risk is more accurately reflected in bond yields.

1. Introduction

For a long time, the Chinese financial market has been characterized by "implicit guarantees," where investors believe that the government or financial institutions will intervene to prevent defaults, especially for SOEs and strategic sectors. This belief led to "rigid redemption," creating a moral hazard where risk and return were decoupled. Consequently, the market failed to price risk accurately, leading to capital misallocation and the buildup of systemic financial risks.

To address these vulnerabilities, Chinese regulatory authorities issued the "Guiding Opinions on Regulating the Asset Management Business of Financial Institutions" (commonly known as the New Asset Management Regulations) in 2018. The core objective of this policy is to break the cycle of rigid redemption, transition toward Net Asset Value (NAV) based products, and ensure that investors bear the risks associated with their investments. This paper examines the effectiveness of these regulations in correcting risk pricing bias within the bond market.

2. Institutional Background and Theoretical Framework

2.1 The New Asset Management Regulations

The New Regulations introduced stringent requirements for financial institutions, including the prohibition of "guaranteed return" products and the mandatory transition to NAV-based valuation. By explicitly forbidding financial institutions from providing backstop guarantees for asset management products, the policy aims to restore the fundamental principle of "high risk, high return."

2.2 Implicit Guarantees and Risk Pricing

In a frictionless market, the yield spread of a bond should reflect its underlying credit risk. However, implicit guarantees act as a form

The long-standing presence of rigid redemptions and implicit guarantee expectations has severely distorted China' s credit rating system, hindering its ability to effectively perform risk screening functions (Jiang et al., 2012). Within an indirect financing system dominated by banks, investors have developed irrational expectations that the government will provide "bottom-line" support for systemically important enterprises. Consequently, a large number of state-owned enterprises (SOEs) characterized by low operational efficiency and high leverage are able to maintain inflated AAA ratings based solely on their asset scale and ownership labels. This allows them to secure significant low-cost financing advantages (Han and Hu, 2015; Zhong et al., 2016). Furthermore, an increasing body of research has found that some highly-rated SOEs exploit this credit advantage by acting as intermediaries in the capital market through shadow banking channels—such as entrusted loans and trust wealth management products—to capture substantial financial arbitrage profits (Allen et al., 2019).

This risk pricing logic, characterized by "inefficiency," is fundamentally rooted in expectations of rigid repayments and implicit guarantees. It is transmitted through unjustifiably inflated credit ratings and results in abnormally low-cost financing. Such a mechanism severely undermines the market-oriented allocation efficiency of capital factors in China. By granting state-owned enterprises (SOEs) an unreasonable advantage in low-cost financing and exceptional interest income, it exerts immense financing and competitive pressure on private enterprises, thereby eroding the operational confidence of private entrepreneurs and stifling market vitality. Furthermore, to a certain extent, this dynamic forces governments at all levels to assume debt risks and pressures that deviate significantly from their actual returns. If allowed to develop unchecked, a large number of state-owned enterprises⋯

State-owned enterprises may lose their competitive drive due to the advantages of low-cost financing and the implicit guarantee of government bailouts. Simultaneously, private enterprises may be forced to exit the market as their operational space is progressively squeezed. Furthermore, in an environment where state-owned enterprise debt defaults occur frequently, the government risks losing public credibility if it becomes unable to sustain large-scale bailouts for these defaults. Ultimately, this dynamic could lead to a dual loss of market efficiency and government credibility.

The "Guiding Opinions on Regulating the Asset Management Business of Financial Institutions" (hereafter referred to as the "New Asset Management Regulations"), jointly issued by the People' s Bank of China and multiple ministries in 2018, has had a significant corrective effect on the phenomenon of distorted capital misallocation. By imposing rigid constraints—such as breaking implicit guarantees, eliminating multi-layer nesting, and reducing leverage—the policy effectively severed non-standard financing channels for inefficient enterprises from the capital supply side. This constituted an exogenous policy shock that broke the market' s expectation of "rigid redemptions" (guaranteed repayments).

The academic community has conducted extensive research into the economic consequences of the New Asset Management Regulations. In recent studies, Wang et al. [?], Wang and Guo [?], and Bai and Li [?] have verified that stringent financial regulation can promote the dynamic adjustment of corporate capital structures and improve the efficiency of credit resource allocation. Furthermore, Yin et al. [?] found that the New Asset Management Regulations effectively inhibit the tendency toward corporate financialization.

However, when exploring the impact of policies on the financing costs of micro-enterprises, a logical contradiction remains that urgently requires explanation. According to theoretical analysis, after the stripping away of implicit guarantees, the financing costs of high-rated state-owned enterprises (SOEs) should experience a relative increase due to the removal of these protections. In practice, however, the focus of a large body of literature remains on the stylized fact that policies have led to "financing difficulties for private enterprises, while the financing costs of state-owned enterprises have decreased rather than increased" [?].

(2022; Bai and Li, 2026). This paper conducts research and discussion centered precisely on this issue. Liu et al. (2022) argue that the efficiency of interest rate transmission is influenced by the interaction between monetary policy and financial regulation. Similarly, this paper contends that the corrective phenomenon of "risk pricing returning to rational levels" —brought about by the "New Asset Management Regulations" breaking expectations of implicit guarantees—was actually masked by the "safe-haven effect" of funds at the macro level. Specifically, following the implementation of the policy, the shock of the 2020 COVID-19 pandemic and the subsequent loose monetary policy caused a massive influx of macro safe-haven capital into state-owned enterprises (SOEs). This led to state-owned···

The overall decline in book financing costs for enterprises has, to a large extent, masked the deep-seated "pricing correction" effects of the New Asset Management Regulations. To explore the process by which policy corrected the authentic risk pricing mechanism of high-rated state-owned enterprises (SOEs) after the breaking of implicit guarantees (rigid redemptions), this paper selects Chinese A-share non-financial listed companies from 2011 to 2024 as a research sample. Utilizing the New Asset Management Regulations as a quasi-natural experiment, we construct a triple-difference (DDD) model. By employing the DDD model, we isolate the safe-haven dividends brought about by macro-level expansionary monetary policy, thereby identifying the net effect of regulatory policy on stripping away the implicit guarantee premiums of high-rated SOEs.

The potential marginal contributions of this paper are reflected in the following aspects:

First, this study re-examines the policy effects of the "New Asset Management Regulations" from the perspective of risk pricing. We propose a novel explanatory framework suggesting that the relative increase in financing costs signifies a rational return to risk pricing. This extends existing academic research regarding the role of eliminating rigid redemptions and implicit guarantees in improving bond market functions \cite{白俊和李玲玲，2026；王永钦和董雯，2023；王茹婷等，2022}.

Second, in terms of perspective and mechanism, this paper breaks through the limitations of previous studies that focused primarily on external interest rate spreads on the liability side. By utilizing the "scissors gap" between net financial expenses and interest costs for the first time, we discuss the inhibitory effect of the New Asset Management Regulations on asset-side arbitrage behavior by State-Owned Enterprises (SOEs). We identify a "de-financialization" effect of the regulations on SOEs that previously engaged in financial arbitrage by exploiting implicit guarantees.

Third, through a heterogeneity analysis based on firm size, this study captures the functional boundaries of implicit guarantees within SOEs. This provides further insight into⋯

To a certain extent, these findings expand the empirical boundaries of the "too big to fail" hypothesis. They also suggest that, within the broader context of dismantling implicit guarantees, the financing advantages previously enjoyed by state-owned enterprises (SOEs) due to their scale have begun to diminish. Furthermore, by analyzing dynamic effects, this study identifies a gradual path through which financial regulatory policies transition from initial establishment to the eventual reversal of market expectations. This process was notably accelerated following the outbreak of a series of substantive default events in 2020. Ultimately, this paper provides micro-level evidence that contributes to a deeper understanding of the incremental nature of China' s financial marketization reforms.

Institutional Background and Theoretical Hypotheses

According to asset pricing theory, a firm' s cost of debt financing is primarily determined by the risk-free interest rate and a risk premium dictated by default risk. However, within the unique context of China's transition economy, implicit government guarantees for state-owned enterprises (SOEs) have emerged as a critical institutional variable in determining debt financing costs [**?**, **?**].

To maintain economic stability and increase employment rates, Chinese local governments often provide de facto bailouts for the debts of state-owned enterprises (SOEs), acting as the ultimate guarantor of last resort. This implicit contract leads investors to perceive the credit of SOEs as a form of quasi-sovereign credit. Consequently, when engaging in financial activities, investors systematically underestimate the default risks associated with state-owned enterprises (Cao, 2023; Li and Li, 2023).

This non-market-oriented pricing logic creates a dual distortion in the market-based capital allocation mechanism. Ex-ante, ownership labels replace financial indicators as the primary anchor for credit rationing, causing market funds to aggregate within inefficient sectors \cite{方军雄，2007; Brandt and Li, 2003}. Ex-post, the existence of soft budget constraints weakens the endogenous motivation for firms to deleverage, improve quality, and increase efficiency, thereby triggering moral hazard \cite{林毅夫和李志赟，2004; Cong et al., 2019}.

(I) The "De-Implicitization" Mechanism of the New Asset Management Regulations and the Correction Hypothesis

In April 2018, the People' s Bank of China, the National Financial Regulatory Administration, and four other departments jointly issued the "Guiding Opinions on Regulating the Asset Management Business of Financial Institutions" (hereinafter referred to as the "New Asset Management Regulations"). This landmark policy aimed to address systemic risks by dismantling the "implicit guarantee" (yinxing danbao) mechanism that had long characterized China' s shadow banking sector.

The core objective of the New Asset Management Regulations is to transition the industry toward a model of "net-value management," where investors bear the actual risks and rewards of their investments. Prior to these regulations, financial institutions often provided de facto principal and interest guarantees—known as implicit guarantees—regardless of the underlying asset performance. This practice distorted risk pricing, encouraged moral hazard, and led to a massive buildup of off-balance-sheet leverage. By mandating the "de-implicitization" of these products, the regulations seek to restore the fundamental principle that "the seller fulfills their duty, and the buyer bears the risk."

Building upon this regulatory shift, we propose a "Correction Hypothesis" regarding the behavior of financial institutions and market participants. We argue that the removal of implicit guarantees triggers a fundamental re-evaluation of asset quality and risk premiums. Specifically, the "de-implicitization" mechanism forces financial institutions to internalize the costs of risk-taking that were previously externalized to the broader financial system or the state. This shift is expected to correct the long-standing misallocation of credit, redirecting capital from low-efficiency "zombie enterprises" that relied on implicit backing toward more productive sectors of the economy. Consequently, the New Asset Management Regulations serve as a critical corrective force, aligning market prices with fundamental risks and enhancing the overall stability of the financial system.

The "Guiding Opinions on Regulating the Asset Management Business of Financial Institutions" aims to sever the shadow banking financing channels that state-owned enterprises have long relied upon. This is achieved through supply-side structural arrangements, such as dismantling capital pools, addressing maturity mismatches, and eliminating the nesting of non-standard assets [?, ?, ?]. This policy represents both a significant improvement in the regulatory framework and a systemic shock to enterprises whose profitability has historically depended on shadow banking models.

This paper argues that the New Asset Management Regulations primarily rectify the risk pricing mechanisms of state-owned enterprises (SOEs) through two distinct pathways. First, by eliminating multi-layer nesting and the operation of capital pools, the regulations effectively sever the off-balance-sheet non-standard financing channels previously available to SOEs.

This forces their financing needs back toward standardized bond or credit markets, thereby increasing the liquidity risk premium of the funds. Second, it establishes a new regulatory orientation aimed at breaking implicit guarantees (rigid redemption) and clarifying the principle that state-owned enterprises (SOEs) must be responsible for their own risks. This approach continuously reduces investor reliance on the quasi-sovereign credit status of SOEs.

In this process, debt costs for enterprises that previously enjoyed the strongest implicit guarantees—due to their AAA credit ratings and state-owned status—will inevitably face the most significant revaluation pressures. The risk premiums of these enterprises, which were previously undervalued, will be accurately reflected in risk pricing, leading to a relative increase in their financing costs.

Based on the aforementioned discussion, this paper proposes Hypothesis H1 (The Rectification Hypothesis): Following the implementation of the New Asset Management Regulations, the comprehensive financial burden on high-rated state-owned enterprises (SOEs) has increased relatively. This shift signifies the stripping away of implicit guarantee premiums and the restoration of the market' s risk pricing function.

(2) The Weakening of "Too Big to Fail" Expectations and Scale Heterogeneity

The "Too Big to Fail" theory posits that the strength of implicit government guarantees for state-owned enterprises (SOEs) is typically an increasing function of the firm's asset scale. As significant participants and influencers in the market, large-scale SOEs exert substantial externalities on their respective industries. Consequently, there is a widespread market perception that the government will inevitably intervene to rescue large SOEs facing severe operational risks. This perception often leads to a deeper distortion in risk pricing for these large entities compared to small and medium-sized enterprises.

As a comprehensive regulatory reform, if the primary role of the "New Asset Management Regulations" is to reconstruct market discipline, it will inevitably impact the "too big to fail" phenomenon among enterprises. Logically, firms with larger asset scales tend to possess greater systemic importance and bargaining power, often leading to implicit guarantees and moral hazard. By tightening oversight and eliminating multi-layer nesting and shadow banking activities, these regulations aim to realign risk with returns, potentially diminishing the preferential treatment historically afforded to massive corporate entities.

For high-rated state-owned enterprises (SOEs), the implicit guarantee premium historically attached to them tends to be higher. Consequently, as the practice of "rigid redemption" (guaranteed repayment) is dismantled, these entities face a more significant credit re-evaluation and a sharper marginal increase in financing costs. This suggests that the corrective effects of policy exhibit a distinct asymmetry across enterprises of different scales.

Based on the aforementioned discussion, this study proposes Hypothesis H2 (Size Heterogeneity Hypothesis): The corrective effect of the New Regulations on Asset Management exhibits size heterogeneity. Specifically, firms with larger asset sizes experience a greater relative adjustment in their financing costs, reflecting a substantive weakening of the "too big to fail" expectation.

3.3 The Dynamic Evolution from "Institutional Establishment" to "Breaking Implicit Guarantee Expectations"

The effectiveness of regulatory policies is characterized by a gradual progression. In 2018, the "New Asset Management Regulations" formally ended the government' s implicit guarantees for state-owned enterprise (SOE) debt at the institutional level. However, the adjustment of market expectations exhibits a certain degree of stickiness. During the initial stages of policy implementation, some investors maintained a wait-and-see attitude, remaining skeptical as to whether the era of rigid repayments and implicit guarantees had truly been brought to an end.

Substantive credit events serve as the critical factor in reversing market expectations. In 2020, a series of substantive defaults by high-rated state-owned enterprises (SOEs), such as Yongcheng Coal and Electricity Holding Group and Huachen Automotive Group, collectively signaled to the market the end of the era of implicit guarantees. These events provided investors with a clear Bayesian updating signal: an enterprise' s state-owned status no longer implies the absence of debt default risk. Consequently, the corrective effects of policy exhibit a gradual onset, reaching their peak only after the occurrence of substantive default events.

Based on the aforementioned discussion, we propose Hypothesis H3 (Dynamic Evolution Hypothesis): The corrective effect of the New Asset Management Regulations is characterized by gradual progression. The corrective impact of the policy initially emerged during the institutional establishment phase in 2018 and was subsequently reinforced following a series of default events in 2020.

3. Research Design

3.1 Sample Selection and Data Sources

The research sample for this study consists of A-share companies listed on the Chinese stock market from 2011 to 2024. This specific period was selected because it spans⋯

The study covers two complete cycles before and after the implementation of the "New Asset Management Regulations" in 2018, which allows for the effective capture of the long-term dynamic effects of this policy shock. To ensure the robustness of the research findings, the data were screened and cleaned according to the following criteria:

(1) **Data Integrity Screening**: Enterprises lacking issuer credit ratings or missing observations for core financial indicators were excluded from the sample.

(2) **Exclusion of Financial Enterprises**: Companies in the financial industry were removed because their asset-liability structures and regulatory requirements differ fundamentally from the real-sector enterprises that are the focus of this study.

(3) **Exclusion of Abnormal Operating Samples**: Companies labeled as ST (Special Treatment), *ST, or PT (Particular Transfer) during the sample period were excluded to eliminate the influence of extreme financial distress or irregular operations.

We excluded observations with abnormal fluctuations in financing costs caused by delisting risks. (4) Winsorization: To mitigate the influence of extreme values on the regression results, all continuous variables were winsorized at the 1st and 99th percentiles. Ultimately, we obtained an unbalanced panel dataset consisting of 15,124 "firm-year" observations. The financial data, credit ratings, and nature of property rights required for this study were sourced from the Wind and CSMAR (China Stock Market & Accounting Research) databases.

2.2 Variable Definition and Measurement

1. Dependent Variable: Net Financial Expenses ($Cost_1$) Following the methodology of Wei Zhihua et al. (2014), this study employs the financial expense method to construct the following indicator:

The net financial expense ratio ($Cost_1$) is calculated as the ratio of financial expenses to the average total assets of the firm. This metric serves as a proxy for the direct financing costs incurred by the enterprise, reflecting the efficiency and burden of its debt servicing relative to its overall asset base.

Financial Expenses i, t

Total Year-End Liabilities i, t

This indicator was selected as the dependent variable because the New Regulations on Asset Management have a significant spillover effect on the credit market. Consequently, the advantage of state-owned enterprises (SOEs) lies not only in their ability to obtain low-interest loans from banks (resulting in lower interest-bearing debt costs) but also in their capacity to leverage their dominant market position to occupy supplier funds, thereby generating substantial non-interest-bearing accounts payable. Relying solely on changes in interest-bearing debt would underestimate the financial advantages of SOEs. Therefore, total end-of-period liabilities are used as the denominator to comprehensively measure the integrated capital cost of utilizing all debt channels. To demonstrate and analyze the deep-seated impacts of the policy from multiple perspectives, this paper incorporates debt financing costs (defined as the ratio of a firm' s interest expenses to its total current and non-current liabilities for the year) into the mechanism analysis.

…the proportion of the mean) as the dependent variable for further correlation analysis and discussion.

2. Core Explanatory Variable

Subject Credit Rating Intensity (Rating): Following the methodology of Poon and Firth (2005) and Chen and Liu (2018), we convert the subject credit ratings disclosed in the corporate annual reports (excluding China Bond Rating Co., Ltd.) into a continuous variable (Xu, 2019). Numerical values are assigned in ascending order according to the credit quality (AAA = 19, AA+ = 18, … , C = 1). Thus, a higher numerical value represents a higher corporate credit rating.

Policy Implementation Timing Variable: Existing research has confirmed that the formal implementation of the "New Asset Management Regulations" in 2018 exerted an exogenous shock on the shadow banking system \cite{郭晔和房芳，2022}. Consequently, this paper selects 2018 as the node for the quasi-natural experiment. The variable takes a value of 1 for the period after 2018 and 0 otherwise.

Ownership structure (SOE): A dummy variable assigned a value of 1 for state-owned enterprises and 0 for non-state-owned enterprises.

3. Control Variables

Following the established literature on debt contracts and asset pricing (Bharath et al., 2008), we incorporate a series of firm-level characteristic variables to control for other factors that may influence asset pricing. These include firm size (Size), leverage ratio (Lev), profitability (Roa), growth potential (Growth), cash flow status (CashRatio), liquidity (Current), tangibility of assets (Tangibility), and Tobin' s Q (TobinQ) (Shen Hongbo et al., 2010).

Dependent variable

Net Financial Expense Ratio (Cost1), Debt Financing Cost (Cost2), Degree of Corporate Financialization (Rsr), Commercial Credit Billization Rate (Ntc), Nature of Property Rights (SOE)

Credit Rating

Credit rating refers to a comprehensive assessment and determination of the creditworthiness of a debt-issuing entity (such as a government, financial institution, or corporation) or a specific debt instrument (such as bonds or commercial paper). This process is typically conducted by independent, professional credit rating agencies. The primary objective of a credit rating is to provide investors with a standardized measure of the probability of default and the potential loss given default associated with a particular credit obligation.

1. Definition and Significance

At its core, a credit rating is an expert opinion on the relative credit risk of an entity or financial obligation. By employing quantitative models and qualitative analysis, rating agencies assign a symbolic grade (e.g., AAA, Baa, or C) to represent the level of credit risk. For the financial markets, credit ratings serve as a critical mechanism for reducing information asymmetry between borrowers and lenders. They facilitate efficient capital allocation, assist in the pricing of risk, and provide a benchmark for regulatory compliance and investment mandates.

2. Rating Categories and Symbols

Credit ratings are generally divided into two broad categories: investment grade and speculative grade (often referred to as "high yield" or "junk bonds").

- **Investment Grade:** These ratings indicate a relatively low to moderate risk of default. For example, in the Standard & Poor' s (S&P) and Fitch scales, ratings from 'AAA' to 'BBB-' are considered investment grade. These entities are generally viewed as having a strong capacity to meet their financial commitments.
- **Speculative Grade:** Ratings at 'BB+' and below suggest higher credit risk. While these instruments offer higher yields to compensate for the increased uncertainty, they are more vulnerable to adverse economic conditions and changes in circumstances.

3. The Rating Process and Methodology

The determination of a credit rating involves a rigorous multi-dimensional analysis. Rating agencies typically evaluate several key factors:

- **Financial Performance:** This includes an analysis of profitability, leverage ratios, liquidity, and cash flow stability.
- **Business Profile:** Analysts examine the entity' s competitive position, diversification, operational efficiency, and the quality of its management team.
- **Macroeconomic Environment:** The rating considers broader economic trends, industry-specific cycles, and the regulatory landscape in which the entity operates.
- **Sovereign Risk:** For international entities, the political and economic stability of the home country is a crucial factor, as it can impact the entity' s ability to access

The ratio of a company' s financial expenses to its total liabilities at the end of the period serves as an indicator of the firm' s comprehensive financing burden. If a company' s interest income and exchange gains exceed its interest expenses, this value will be negative. Furthermore, the cost of debt financing is calculated as the ratio of the company' s interest expenses to the average value of its total short-term and long-term liabilities for the current year.

Interest income to firm size ratio. Notes payable / (Notes payable + Accounts payable). SOE dummy variable, which takes the value of 1 if the firm is a state-owned enterprise and 0 otherwise. The issuer credit rating disclosed by the listed company between April and June of that year, represented as a numerical credit rating score after assignment processing.

New Asset Management Regulations (Post), Leverage Ratio (Lev), Return on Assets (Roa), Firm Size (Size), Tobin' s Q (TobinQ), Tangibility Ratio (Tangibility), Cash Flow to Current Liabilities Ratio (Cashratio), Operating Revenue Growth Rate (Growth), Current Ratio (Current)

A dummy variable, taking the value of 1 for periods after 2018 and 0 otherwise. The ratio of total liabilities to total assets. (Total Profit + Financial Expenses) / Average Total Assets. The natural logarithm of total assets. The market value of capital divided by replacement cost. (Total Assets - Net Intangible Assets - Net Goodwill) / Total Assets. (Annual Net Operating Cash Flow / Current Liabilities at year-end) $\times$ 100%. The year-on-year growth rate of operating income. Current Assets / Current Liabilities.

3.3 Model Specification: Triple Differences (DDD)

To further mitigate potential endogeneity issues arising from omitted variables and to rigorously test the causal impact of the policy, this study employs a Triple Differences (DDD) model. While the standard Difference-in-Differences (DID) approach accounts for time-invariant differences between the treatment and control groups, it may still be susceptible to time-varying shocks that affect different regions or industries heterogeneously. By introducing a third dimension of comparison, the DDD model allows us to control for these additional layers of unobserved factors, thereby providing more robust empirical evidence.

The DDD model is specified as follows:

$$Y_{it} = \alpha + \beta(Treat_i \times Post_t \times Group_i) + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

In this specification, Y_{it} represents the outcome variable of interest for entity i at time t. $Treat_i$ is a dummy variable indicating whether an entity belongs to the treatment group affected by the policy, while $Post_t$ is a temporal dummy variable that takes the value of 1 for the period after the policy implementation and 0 otherwise. The additional term $Group_i$ represents the third dimension of differentiation, such as industry characteristics or regional attributes, which helps isolate the specific policy effect from broader macroeconomic or sectoral trends.

The coefficient of interest is β, which captures the triple-difference effect. A statistically significant β indicates that the policy had a differential impact on the treatment group relative to the control group, even after accounting for the variations across the third dimension. X_{it} denotes a vector of control variables, μ_i represents entity-fixed effects, λ_t represents time-fixed effects, and ϵ_{it} is the idiosyncratic error term. This multi-layered fixed-effects structure ensures that the estimation results are not biased by persistent unobserved heterogeneity or common temporal shocks.

Following the research design of Gruber (1994), we construct the following triple differences (DDD) model. Compared to traditional difference-in-differences (DID) approaches, the DDD model allows for more robust causal inference by controlling for potential confounding trends across different groups.

The model is specified as follows:

$$\begin{aligned}Y_{ist} =& \beta_0 + \beta_1(Treat_i \times Post_t \times Group_s) + \beta_2(Treat_i \times Post_t) \\ &+ \beta_3(Treat_i \times Group_s) + \beta_4(Post_t \times Group_s) \\ &+ \beta_5 Treat_i + \beta_6 Post_t + \beta_7 Group_s + \epsilon_{ist}\end{aligned}$$

In this specification, Y_{ist} represents the outcome variable of interest for individual i in group s at time t. The variable $Treat_i$ is a dummy variable indicating the treatment status, $Post_t$ is a binary indicator for the post-treatment period, and $Group_s$ represents the specific subgroup classification. The coefficient of interest, β_1, captures the triple difference effect, identifying the differential impact of the policy across treatment and control groups while accounting for variations across subgroups and time. This approach effectively filters out time-varying shocks that might affect the treatment and control groups differently but are common to the specific subgroups.

The Difference-in-Differences (DID) and Difference-in-Difference-in-Differences (DDD) models are capable of disentangling the "safe-haven effect" induced by policy at the macro level from the "corrective effect" occurring at the micro level within the regression results.

Costi,t = \$ \$0 + \$ \$1(Ratingi,t × SOEi × Postt) + \$ \$2 (Ratingi,t × SOEi) + \$ \$3 (Ratingi,t × Postt) + \$ \$4 (SOEi × Postt) + \$ \$5 Ratingi,t + γXi,t + \$ \$1(Yeart × SOEi) + μi + δt + ϵi,t

The coefficient β_1 represents the reduction in implicit guarantees for high-rated state-owned enterprises (SOEs) following the implementation of the policy, relative to the period prior to its introduction.

Guarantee premium; it can also represent the relative increase in financing costs for high-rated state-owned enterprises (SOEs) compared to low-rated SOEs following the implementation of a policy. If β_1 is significantly negative, it indicates that the policy has effectively reduced the credit spreads of low-rated SOEs, thereby narrowing the "rating-based spread" within the SOE sector. This suggests that the implicit guarantee associated with government backing has been recalibrated, leading to a market-driven reassessment of credit risk across different rating tiers.

1 为正，则说明监管政策打破刚兑后，由于刚

The reduction in the risk guarantee premium resulting from credit exchange confirms that hypothesis H1 holds true. In this context, $X_{i,t}$ represents the control variables.

is the firm-level fixed effect, which absorbs time-invariant characteristics at the firm level.

1. Introduction

The impact of corporate culture on financing costs is a critical area of study, particularly regarding how internal organizational values interact with external financial constraints. Corporate culture serves as an informal institutional mechanism that can either mitigate or exacerbate information asymmetry between firms and investors. By fostering transparency and ethical behavior, a strong corporate culture may reduce the risk premium demanded by lenders, thereby lowering the cost of capital. Conversely, a toxic or misaligned culture can lead to agency problems and increased monitoring costs.

Furthermore, corporate culture acts as a stabilizing force, allowing firms to absorb macroeconomic fluctuations. During periods of economic volatility, companies with resilient cultural frameworks are better positioned to maintain operational stability and investor confidence. This buffering effect is essential for navigating systemic shocks that might otherwise lead to severe financial distress.

1.1 Ownership Trends and Financing

The study also accounts for trends in corporate ownership (Y_{it}), which significantly influence a firm' s access to capital markets. Ownership structure—whether state-owned or private—often dictates the level of implicit government guarantees and the degree of scrutiny from financial institutions. As ownership trends evolve, they interact with corporate culture to shape the overall financing environment for the enterprise. Understanding these dynamics is crucial for assessing how micro-level organizational traits and macro-level economic shifts collectively determine a firm' s financial health and strategic positioning.

Methodology

Fixed Effects Model

In this study, we employ a fixed effects model to account for unobserved heterogeneity that may be correlated with the independent variables. Specifically, to control for macroeconomic shocks, policy shifts, and systemic trends that affect all entities simultaneously, we incorporate year fixed effects.

By including year fixed effects, we account for time-specific factors that are constant across individuals but vary over time. This approach ensures that the estimated coefficients are not biased by temporal shocks, such as economic cycles or national regulatory changes, which might otherwise lead to spurious correlations. The model is specified as follows:

$$Y_{it} = \alpha + \beta X_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

where Y_{it} represents the dependent variable for entity i in year t, X_{it} denotes the vector of explanatory variables, μ_i represents entity-specific fixed effects, λ_t denotes the year fixed effects, and ϵ_{it} is the idiosyncratic error term. This structure allows us to isolate the internal variation within the data, providing more robust causal inferences.

To enhance the robustness of the regression results, additional control variables have been incorporated into the model.

Abstract

In this study, we investigate the impact of integrating core components within the proposed framework. By incorporating these elements, the system demonstrates significant improvements in performance and stability. Our analysis focuses on the interaction between the added modules and the existing architecture, highlighting the optimization of computational efficiency and the enhancement of feature representation.

Introduction

The development of robust models in machine learning requires a careful balance between architectural complexity and generalization capability. Recent advancements have shown that the strategic addition of core layers can lead to substantial gains in accuracy. In this paper, we present a detailed evaluation of these additions, specifically focusing on how they influence the overall learning dynamics.

[Figure 1: see original paper]

1.1 Methodology

Our approach involves the systematic integration of core modules designed to refine the input data processing pipeline. By utilizing $\mathcal{F}$ as our primary transformation function, we ensure that the spatial features are preserved while reducing noise. The relationship between the input x and the transformed output $\tilde{x}$ is defined as follows:

$$\tilde{x} = \mathcal{F}(x, \theta)$$

where θ represents the learnable parameters of the core module. As noted in [**?**], such transformations are essential for handling high-dimensional datasets effectively.

1.2 Experimental Results

The experimental results indicate that after adding the core components, the model' s convergence rate improved by approximately 15%. summarizes the comparative performance across different benchmarks. We observe that the inclusion of $\bar{b}$ as a regularization term further stabilizes the training process, preventing overfitting in complex scenarios.

$$\mathcal{L}_{total} = \mathcal{L}_{task} + \lambda \cdot \bar{b}$$
$$\bar{b} = \sum_{i=1}^{n} \|w_i\|^2$$

As shown in (1), the total loss function $\mathcal{L}_{total}$ balances the task-specific loss with the regularization term, ensuring that the model maintains a high degree of interpretability and performance.

Conclusion

In conclusion, the addition of core modules provides a significant boost to the framework' s effectiveness. Future work will explore the scalability of this approach to even larger datasets and more diverse machine learning tasks. The findings presented here lay the groundwork for more efficient and reliable model architectures in the field of deep learning.

The t-statistics of the explanatory variables are significantly higher, and the coefficients have increased in magnitude. Furthermore, this model employs cluster-robust standard errors at the firm level.

4. Empirical Results and Analysis

4.1 Descriptive Statistics

(Mean)

(Min)

(P50)

(Max)

Net Financial Expense Ratio

Cost1

Cost of Debt Financing

Cost2

Corporate Credit Rating

Corporate credit rating refers to the comprehensive assessment and determination of an enterprise' s creditworthiness and its ability to fulfill financial obligations. This process involves a systematic analysis of the entity' s operational health, financial position, management quality, and external environment to provide an objective measure of default risk.

1. Definition and Significance

The primary objective of a corporate credit rating is to evaluate the probability that a borrower will fail to meet its debt obligations in full and on time. These ratings serve as a critical benchmark for investors, creditors, and regulators in the financial markets. By quantifying credit risk, ratings facilitate efficient capital allocation, assist in the pricing of debt instruments, and provide a standardized language for risk communication across different sectors and geographies.

2. Evaluation Framework

The assessment of corporate credit typically employs a multidimensional framework that integrates both qualitative and quantitative factors:

- **Business Profile:** This includes an analysis of the industry' s competitive landscape, the company' s market position, diversification of products and services, and the stability of its supply chain.
- **Financial Profile:** Analysts examine key financial metrics such as profitability, leverage ratios, liquidity, and cash flow adequacy. Common indicators include the Debt-to-EBITDA ratio, interest coverage ratios, and free cash flow generation.

- **Management and Governance:** The quality of the leadership team, strategic execution capabilities, internal control systems, and corporate governance structures are scrutinized to assess long-term stability.
- **External Environment:** Macroeconomic conditions, regulatory changes, and potential government support (especially for state-owned enterprises) are factored into the final rating.

3. Rating Scales and Symbols

Credit ratings are typically expressed through a standardized system of letter grades. While specific symbols may vary slightly between agencies, the general hierarchy is as follows:

- **Investment Grade:** Ratings such as AAA, AA, A, and BBB indicate a relatively low risk of default. These entities are considered to have strong to adequate capacities to meet their financial commitments.
- **Speculative Grade (High Yield):** Ratings of BB, B, CCC, and below suggest higher credit risk. These entities are more vulnerable to adverse economic conditions and have a higher probability of default.

4. The Role of Technology in Credit Rating

In recent years, the field has seen a significant shift toward the integration of advanced analytical techniques. Traditional expert-based models are increasingly being supplemented or replaced by machine learning

Rating

Degree of corporate financialization

Commercial credit securitization rate

Asset-liability ratio

Return on Total Assets (ROA)

Tobin’ s Q value

TobinQ

Operating Income Growth Rate

Growth

Cash Flow to Current Liabilities Ratio

CashRatio

Current

Tangible Asset Ratio

Tangibility

Baseline Regression Analysis

To ensure the reliability and authenticity of the empirical results, the reported regression findings transition gradually from column (1) to column (3), culminating in a complete model that incorporates multidimensional fixed effects and specific time trends.

The results indicate that the coefficient of the double interaction term $SOE \times Post$

is significantly negative at the 1% level

with a value of -0.0260. This suggests that state-owned enterprises (SOEs) as a whole enjoyed a financing dividend under the influence of macro-deleveraging, characterized by a downward trend in financing costs. This finding is consistent with the research of Bai and Li (2026). This dividend is primarily driven by the "safe-haven effect" of capital at the macroeconomic level. However, the triple interaction term $Rating \times SOE \times Post$, which is the primary focus of this study,

is significantly positive at the 1%

significance level (0.0015). This indicates that the New Regulations on Asset Management stripped away approximately 0.15% (15 bps) of the implicit guarantee premium from high-rated SOEs, reflecting a structural "pricing correction" brought about by policy impacts at the micro level. Although the overall financing costs for SOEs decreased, the magnitude of this decline was significantly smaller for high-rated SOEs compared to low-rated ones. Consequently, prior to the introduction of the New Regulations on Asset Management, high-rated SOEs enjoyed long-term excess low-cost financing due to the advantage of rigid debt redemption backed by government credit. Following the implementation of these regulations, this "excess dividend" resulting from inflated ratings was significantly curtailed. The positive DDD coefficient effectively represents

an offset to the safe-haven dividend associated with SOE status. This is consistent with the findings of Kou and Pan (2020), demonstrating that the market is now demanding more reasonable risk compensation from high-rated SOEs, and risk pricing is reverting toward its true level.

No control variables

Controlling for ownership-specific time trends

0.0013**

0.0008**

0.0015***

(2.51)

(2.17)

(2.86)

-0.0002**

(2.46)

(0.88)

(-1.62)

(-1.21)

(1.39)

(0.14)

-0.0231**

-0.0144**

-0.0260***

(-2.56)

(-2.11)

(-2.80)

-0.0008***

(-2.60)

(-0.86)

Rating

Individual Fixed Effects

Time Fixed Effects

Sample Size (N)

14,447

14,447

Adj. R-squared

Note: Values in parentheses represent *t*-statistics. , , *and* denote statistical significance at the 1%, 5%, and 10% levels, respectively. The same applies to the following tables.

3.3 Dynamic Effects and Parallel Trend Test

In this section, we conduct a parallel trend test to verify the robustness of the Triple Differences (DDD) model. Using 2017 as the base year, we employ the event study method to map the dynamic effects of the DDD term for the period from 2014 to 2024, as illustrated in Figure 1 [Figure 1: see original paper]. Figure 1 demonstrates···

The results demonstrate the statistical robustness of the DDD model while simultaneously reflecting the process by which the risk pricing mechanism is being reshaped.

1 Parallel Trend Test

To ensure the validity of the difference-in-differences (DID) estimation, the treatment and control groups must exhibit a "stable trend" prior to the implementation of the policy. As shown in [Figure 1: see original paper], the coefficients of the interaction terms for the period preceding the official implementation of the New Asset Management Regulations (2014–2017) are not statistically significant. This indicates that there was no systematic difference in the outcome variables between the treatment and control groups before the policy intervention, thereby satisfying the parallel trends assumption required for causal inference.

The parallel trends test results indicate that prior to the policy implementation, the estimated coefficients fluctuated around the zero axis, and their 95% confidence intervals all included the value of zero (the dashed lines in represent the 95% confidence intervals). This demonstrates that there were no significant systematic differences between the treatment group and the control group before the policy took effect.

The release of policy effects exhibits a progressive character. The gradual increase in the DDD coefficients suggests that the risk pricing mechanism is not corrected by policy effects instantaneously. Instead, it evolves as investors undergo a process of learning and adaptation, triggered by a series of significant default events.

These findings highlight the critical Bayesian learning nodes used for reevaluating financing risks. The introduction of the "New Asset Management Regulations" in 2018 led to only a marginal increase in the DDD coefficient, primarily because market expectation adjustments exhibit a degree of stickiness, leaving investors in a "wait-and-see" state. In contrast, the most severe fluctuations and peak values of the DDD coefficient occurred in 2020. This indicates that the substantive defaults of state-owned enterprises, such as Yongcheng Coal and Electricity Holding Group and Huachen Automotive Group in 2020, dealt a decisive blow to market expectations regarding "rigid redemptions" (guaranteed repayments). This developmental trend confirms the previously proposed "dynamic learning mechanism" (Hypothesis H3).

During the COVID-19 pandemic from 2020 to 2022, the DDD (Difference-in-Difference-in-Differences) coefficient exhibited a gradual downward trend. This indicates that the corrective effect of the policy weakened year by year. This phenomenon can be attributed to the phased easing policies implemented by the government during the pandemic, which were aimed at maintaining economic stability.

This phenomenon was jointly driven by the specific objectives of the "New Asset

Management Regulations" and a general sense of risk aversion among investors. During this period, the actual debt financing costs for state-owned enterprises (SOEs) decreased due to the influx of safe-haven capital. This trend diverged significantly from the new risk premium levels established under the framework of the "New Asset Management Regulations."

However, following the COVID-19 pandemic and the conclusion of the "New Asset Management Regulations" transition period at the end of 2022, the DDD coefficient rebounded rapidly, returning to high levels by 2024. This trend demonstrates that the impact of the "New Asset Management Regulations" on the risk pricing mechanism of corporate debt financing is robust and will not be reversed by short-term external shocks.

5. Identification Assumptions and Robustness Checks

5.1 Parallel Trend Test and Analysis of Dynamic Effects

A fundamental prerequisite for employing the Difference-in-Differences (DID) method is that the treatment and control groups must satisfy the parallel trend assumption. Specifically, in the absence of the policy intervention, the change in the level of digital transformation between the treatment group (enterprises in the pilot zones) and the control group should follow a consistent trend. To verify this, we employ the Event Study Approach to test for parallel trends and analyze the dynamic effects of the policy. The specific model is constructed as follows:

$$\text{Digital}_{i,t} = \alpha + \sum_{k=-4}^{4} \beta_k D_{i,t}^k + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}$$

In this model, $D_{i,t}^k$ is a series of dummy variables representing the periods before and after the establishment of the pilot zones. We define $k = 0$ as the year the pilot zone was established; $k < 0$ represents the k-th year prior to the establishment, and $k > 0$ represents the k-th year following it. To avoid perfect multicollinearity, the year prior to the policy implementation ($k = -1$) is excluded as the reference period.

[Figure 1: see original paper]

[Figure 1: see original paper] illustrates the results of the parallel trend test. The coefficients β_k for the periods prior to the policy implementation ($k < -1$) are not statistically significant, and their values are close to zero. This indicates that there was no significant difference in the development of digital transformation between the treatment and control groups before the establishment of the pilot zones, thereby satisfying the parallel trend assumption. Following the implementation of the policy ($k \geq 0$), the coefficients β_k become significantly positive and exhibit an upward trend over time. This suggests that the "National Comprehensive Big Data Strategy Pilot Zones" have a sustained promotional effect on corporate digital transformation, with the policy' s impact gradually intensifying over the sample period.

5.2 Placebo Test

To further rule out the possibility that the observed effects are driven by unobservable omitted variables or random factors, we conduct a placebo test using a permutation test approach. Specifically, we randomly assign the "pilot zone"

Placebo Test

To verify the reliability of the aforementioned conclusions and exclude the interference of unobservable factors, this study conducts a non-parametric permutation test by randomly reassigning the treatment group. Specifically, while keeping other variables constant, we randomly shuffle the ownership attributes (SOE) of firms across the cross-sectional dimension to generate a "pseudo-treatment group." We then re-estimate the triple-difference (DDD) regression based on these randomized ownership assignments. This procedure was repeated 1,000 times to obtain an empirical distribution of 1,000 pseudo-coefficient estimates. The empirical results yield a p-value of only 0.008, indicating that the baseline regression results of this study are not driven by chance.

2.2 Measurement Sensitivity Analysis

The empirical results of this study may be subject to interference from the specific measurement methods used for the dependent variable or the exogenous shocks caused by major public health emergencies (such as COVID-19) during the sample period. To further verify the robustness of our findings and explore the underlying mechanisms behind rising financing costs, this paper employs a cross-validation strategy. This strategy involves two primary approaches: "alternative measurement of the dependent variable" and "stress testing under pandemic shocks."

The outbreak of the COVID-19 pandemic in 2020 occurred within the sample period, triggering significant volatility across global capital markets, including those in China.

⋯ "risk aversion" (Chen Guojin et al., 2018). To investigate whether this significant macroeconomic shock affects the conclusions of this paper, we conduct an analysis by comparing the regression results of the full sample (including the pandemic years) with those of a subsample excluding the pandemic years (2011–2019), as presented in .

The dependent variable $Cost1$ used in the baseline regression includes non-interest-bearing commercial credit, such as accounts payable, in its denominator. Consequently, this measure may fail to accurately capture the specific impact of policies on a firm' s debt financing costs. To address this, following existing literature, this paper constructs a more refined debt financing indicator, $Cost2$, defined as the ratio of interest expenses to the sum of short-term and long-term liabilities. By excluding the influence of operating liabilities on financing costs, this indicator serves as a precise measure of the actual cost incurred by firms when obtaining "interest-bearing debt" within financial markets.

A cross-sectional comparative analysis was conducted for the two dependent variables across two distinct periods, leading to two primary findings. First, there is evidence of intensified credit risk-off behavior at the macro level. For both dependent variables within the full sample, the S value⋯

The absolute value of the coefficient is significantly larger than that of the pre-pandemic sample. This indicates that when faced with the impact of major risk events, capital flows toward state-owned enterprises (SOEs) at an accelerated rate in search of a "safe haven" due to their superior fundamentals and institutional advantages. Consequently, the overall financing costs for SOEs exhibit a downward trend.

Second, the pricing mechanism continues to function at the micro level: despite the massive macro-level inflow of capital into SOEs (the safe-haven effect), the core interaction term (the DDD coefficient) representing the market-oriented pricing mechanism demonstrates strong resilience across the full sample. The coefficient increased from 0.0013 in the partial sample to 0.0015 in the full sample and did not weaken due to the impact of the pandemic. This suggests that the "risk-based pricing" mechanism established by the "New Asset Management Regulations" remains robust.

The "correction mechanism" possesses a very strong endogenous momentum. This observation aligns with the core argument of this paper: even within a macro environment where the pandemic triggered "credit risk aversion" and capital flowed toward state-owned enterprises (SOEs) out of a "safe-haven motive," the corrective role of policy did not fail. Instead, the market remained capable of differentiating among SOEs, specifically identifying those with inflated ratings and excessive reliance on implicit guarantees. The coexistence of macro-level "risk aversion" and micro-level "price correction" further demonstrates the substantive improvement in the pricing efficiency of China' s capital market since 2018.

Dependent variable

Net Financial Expense Ratio (Cost1)

Net Financial Expense Ratio (Cost1)

Cost2 (Explicit Financing Cost)

Cost2 (Explicit Financing Costs)

(Excluding pandemic years)

Abstract

This study investigates the impact of the COVID-19 pandemic on global economic structures and supply chain resilience using advanced machine learning techniques. By analyzing multi-source data spanning the pre-pandemic, peak-pandemic, and recovery phases, we identify key vulnerabilities in international trade networks. Our findings suggest that while the pandemic caused significant short-term disruptions, it also accelerated the adoption of digital transformation and remote collaboration technologies, leading to a fundamental shift in industrial productivity models.

Introduction

The emergence of the COVID-19 pandemic represented an unprecedented exogenous shock to the global economy. Unlike traditional financial crises, this period was characterized by simultaneous supply and demand shocks, compounded by logistical bottlenecks and labor shortages. Understanding the long-term implications of these "pandemic years" is crucial for developing robust economic policies and corporate strategies in the post-pandemic era.

[Figure 1: see original paper]

Recent literature has extensively documented the immediate effects of lockdowns on GDP growth and employment. However, there remains a gap in understanding how structural shifts in consumer behavior and firm-level operations have persisted beyond the initial crisis. This paper utilizes deep learning architectures to model these complex transitions, providing a more granular view of economic recovery patterns across different sectors.

Methodology

Data Collection and Pre-processing

We compiled a comprehensive dataset including macroeconomic indicators, high-frequency mobility data, and corporate financial reports. To ensure consistency across the pandemic years, we applied normalization techniques to account for seasonal variations and government intervention policies.

The primary objective function for our predictive model is defined as:

$$\min_{\theta} \sum_{i=1}^{N} \mathcal{L}(y_i, f(x_i; \theta)) + \lambda \|\theta\|^2$$

where y_i represents the economic output, $f(x_i; \theta)$ is the neural network mapping, and λ is the regularization parameter to prevent overfitting during volatile periods.

Model Architecture

We employed a Long Short-Term Memory (LSTM) network to capture the temporal dependencies inherent in the time-series data. Given the non-linear nature of the pandemic' s impact, the hidden state h_t is updated as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

(Excluding pandemic years)

Abstract

This study investigates the impact of the COVID-19 pandemic on global economic structures and supply chain resilience using advanced machine learning techniques. By analyzing multi-source datasets spanning the pre-pandemic and pandemic periods, we identify key vulnerabilities in international trade networks and evaluate the efficacy of various policy interventions. Our findings suggest that while the pandemic induced significant short-term disruptions, it also accelerated the adoption of digital transformation and remote collaboration technologies, leading to a fundamental shift in labor market dynamics.

1. Introduction

The emergence of COVID-19 in late 2019 triggered an unprecedented global health crisis that rapidly evolved into a multifaceted socio-economic challenge. Unlike previous economic downturns, the pandemic-induced recession was characterized by simultaneous supply and demand shocks, further complicated by varying national lockdown strategies and public health responses. Understanding the long-term implications of these "pandemic years" is crucial for developing robust economic models and preparing for future systemic risks.

[Figure 1: see original paper]

2. Methodology

To capture the complexities of the pandemic' s impact, we employ a hybrid modeling approach combining traditional econometric analysis with deep learning architectures. Specifically, we utilize Long Short-Term Memory (LSTM) networks to process time-series data related to industrial output, consumer spending, and mobility indices.

2.1 Data Collection and Preprocessing

Our dataset integrates information from the World Bank, the International Monetary Fund (IMF), and real-time mobility data provided by major technology platforms. We define the "pandemic period" as spanning from January

2020 to December 2022 to account for the multiple waves of infection and the subsequent rollout of vaccination programs.

The primary objective function for our predictive model is defined as:

$$\min_{\theta} \sum_{t=1}^{T} \mathcal{L}(y_t, f(x_t; \theta)) + \lambda \|\theta\|^2$$

where y_t represents the observed economic indicators at time t, $f(x_t; \theta)$ is the neural network output, and λ is the regularization parameter to prevent overfitting during periods of high volatility.

3. Results and Discussion

Our analysis reveals a heterogeneous recovery pattern across different sectors. While the service industry, particularly tourism and hospitality, suffered prolonged contractions, the information technology and e-commerce sectors experienced exponential growth.

3.1 Supply Chain

Rating × SOE ×

0.0013** (2.33)

0.0015*** (2.86)

0.0023** (2.22)

0.0030*** (2.75)

SOE × Post

-0.0235** (-2.36)

-0.0260*** (-2.80)

-0.0468*** (-2.66)

-0.0572*** (-3.08)

Rating

-0.0018**

-0.0013*

(1.19)

(-0.86)

(-2.47)

(-1.67)

Sample size (N)

6,910

14,447

6,910

14,447

Adj. R-squared

(3) Dummy Variable Treatment of Credit Ratings In the baseline regression analysis, a linear assignment assumption was applied to the credit rating intensity, which serves as the primary explanatory variable.

However, in practice, credit ratings often exhibit non-linear characteristics. To ensure that the linear assumption of credit ratings does not bias the research findings, this study re-conducts the experiments by converting the credit rating intensity into a dummy variable, *Rating_Dummy*. Based on the descriptive statistics, the median credit rating is 17; therefore, ratings of AAA, AA+, and AA (which correspond to values greater than or equal to 17) are assigned a value of 1, while all other ratings are assigned a value of 0. The regression formula is as follows:

Costi,t = \$ \$0 + \$ \$1(Rating_{Dummyi},t $\times$ SOEi $\times$ Postt) + \$ \$2 (Rating_{Dummyi},t $\times$ SOEi) + \$ \$3 (Ratingi,t $\times$ Postt) + \$ \$4 (SOEi $\times$ Postt) + \$ \$5 Rating_{Dummyi},t + γXi,t + \$ \$1 (Yeart $\times$ SOEi) + μi + δt + ϵi,t

The results (Table 5) show that the coefficient of the core interaction term remains significantly positive at the 1% level (0.0059).

This indicates that the conclusions of this study do not depend on the continuity assumption of the credit rating variable.

Dependent Variable

Cost1 (Net Financial Expense Ratio); Rating set as a dummy variable (1 if AAA/AA+/AA, 0 otherwise); 0.0059*** (2.97); 14,447

Core Variable Form: Rating_{Dummy} $\times$ SOE $\times$ Post; Two-way Fixed Effects; Sample Size (N); Adj. R-squared

(4) Freezing Pre-treatment Status. Considering that the core explanatory variable, Rating, may have been influenced by policy changes following the implementation of the "New Asset Management Regulations" in 2018, we address potential endogeneity concerns. To exclude the endogenous influence of rating changes, we redefine the core explanatory variable, Rating

(Issuer Credit Rating), as a constant indicator based on the 2017 baseline year and re-estimate the regression. Table 6 reports the results.

Core Explanatory Variable: Pre-treatment Constant Credit Rating

Dependent Variable

Cost1 (Net Financial Expense Ratio)

Core Variable Form

Rating_{base} represents the credit rating in 2017

Rating_{base} × SOE × Post; Two-way Fixed Effects; Sample Size (N); Adj. R-squared

0.0013** (2.50) 11,494

The results indicate that the findings remain significant even after stripping away the impact of the "New Asset Management Regulations" on the credit rating system.

The coefficient is positive and has not undergone significant changes. This suggests that the core explanatory variable, *Rating*, does not suffer from serious endogeneity issues.

5. Robustness Test Based on PSM Samples and Alternative Dependent Variables

To eliminate potential sample self-selection bias and measurement bias from using a single indicator in the baseline regression, we conduct a joint robustness test by combining Propensity Score Matching (PSM) with alternative dependent variables. Based on the financial characteristics of the treatment and control groups in 2017, we performed 1:1 nearest neighbor matching. The results show that the standardized deviations of covariates—such as size and leverage—for high-rated SOEs and ordinary enterprises converged significantly toward zero. This process yielded a balanced matching sample where inherent characteristics exhibit no heterogeneity.

Based on this matched sample, we re-ran the regressions using the original dependent variable ($Cost1$) and an alternative measure of debt financing cost ($Cost2$). presents the regression results. Columns (1) and (2) use $Cost1$ as the dependent variable, while columns (3) and (4) use $Cost2$. The coefficient of the core explanatory variable $Rating \times SOE \times Post$ is significantly positive in columns (2), (3), and (4). Notably, in column (4), the significance level increases to 1% (coefficient = 0.0049, $t = 2.65$). The model includes $Rating \times SOE \times Post$, $SOE \times Post$, and $rating$ with two-way fixed effects.

Dependent Variable: $Cost1$ (1) Baseline Controls (0.72) (-0.85) -0.0008* (-1.73)

(2) Controlling for Trends 0.0018** (1.99) -0.0326** (-2.06) (0.27)

Dependent Variable: $Cost2$ (3) Baseline Controls 0.0023** (2.53) -0.0466*** (-3.09) -0.0016* (-1.92)

(4) Controlling for Trends 0.0049*** (2.65) -0.0914*** (-2.92) (0.27)

The significant increase is neither a random phenomenon caused by extreme sample characteristics nor is it limited to a specific measurement method of financing costs. The empirical conclusions of this paper possess high internal validity and robustness.

6. Further Discussion

6.1 Mechanism Analysis: The "Structural Divergence" Between Explicit Costs and Comprehensive Burden

$Cost1$ (net financial expense ratio) and $Cost2$ (explicit interest cost) measure corporate financing costs from two different dimensions. By comparing the dynamic trend charts of $Cost1$ and $Cost2$ ([Figure 3: see original paper]), we observe a "structural divergence" between the dynamic paths of the two dependent variables after 2022, manifested as a "scissors gap."

When the net financial expense ratio ($Cost1$: the ratio of financial expenses to total liabilities at the end of the period) is set as the dependent variable, the DDD coefficient shows a significant upward trend during 2023-2024. Conversely, when explicit financing cost ($Cost2$: the ratio of interest expenses to the average of current year long-term and short-term debt) is used as the dependent variable, the DDD coefficient tends to converge during the same period. This phenomenon—where the net financial expense ratio rises while explicit financing costs relatively decline—reveals a deeper mechanism of the "New Asset Management Regulations" :

First, "de-financialization" on the capital supply side. A primary objective and function of the "New Asset Management Regulations" is to strictly restrict profit-seeking activities where enterprises utilize their financial advantages to act as shadow banks. Before the policy was implemented, many state-owned enterprises (SOEs) frequently purchased non-standard assets and engaged in loan transfers to earn interest income, thereby lowering their own net financing costs.

However, arbitrage opportunities arising from "funds circulating within the financial system" were significantly restricted after the policy' s implementation. This led to a sharp decline in interest income (the subtraction component in the numerator of $Cost1$), which passively pushed up net financial expenses and caused $Cost1$ to rise. Therefore, the increase in the net financial expense ratio during 2023-2024 essentially reflects the effectiveness of the "New Asset Management Regulations" in curbing corporate arbitrage and financialization activities.

To further illustrate this "de-financialization" mechanism, this paper constructs a proxy for the degree of corporate financialization:

The indicator *Rsr* (the ratio of interest income to total assets) is used to establish a Triple Difference (DDD) model identical to the baseline regression. Since interest income is itself a component of net profit, we exclude ROA from the set of control variables $X_{i,t}$ to prevent over-controlling, while keeping all other control variables constant to obtain $X'_{i,t}$:

Rsri,t = \$ \$0 + \$ \$1 (Ratingi,t × SOEi × Postt) + \$ \$2(Ratingi,t × SOEi) + \$ \$3 (Ratingi,t × Postt) + \$ \$4(SOEi × Postt) + \$ \$5Ratingi,t + γX' i,t + \$ \$1 (Yeart × SOEi) + μi + δt + ϵi,t

The regression results presented in indicate that the coefficient β_1 is negative. In the parallel trends test, the assumption of pre-treatment stationary trends is satisfied, while the post-treatment coefficients are significant. These findings suggest that the implementation of the policy has exerted a significant inhibitory effect on the target variable.

The number began to decline and became significantly negative during the 2023-2024 period (Appendix Figure 1). The p-value for the placebo test was 0.042 ([Figure 2: see original paper]), indicating that following the implementation of the "New Asset Management Regulations," the proportion of interest income to total assets for high-rated state-owned enterprises (SOEs) decreased significantly.

According to the accounting equation, $Cost1$ is defined as the ratio of the difference between interest expenses and interest income to total liabilities. The "de-financialization" of these enterprises led to a reduction in interest income, which in turn increased the numerator of the $Cost1$ calculation, thereby raising the net financial expense ratio ($Cost1$). These results demonstrate that the arbitrage space for SOEs has been substantially compressed, verifying the effectiveness of the "New Asset Management Regulations" in promoting the "de-financialization" of state-owned enterprises.

The dependent variable is Rating × SOE × Post.

Specific ownership trends, individual fixed effects, time fixed effects, and sample size (N).

Rsr (Ratio of interest income to total assets) & -0.0002^{**} (-1.96) & (0.43) & 0.0001^{**} (2.01) & 0.0026^{*} (1.94) & Yes / Yes & 14,456

[TABLE:N]

The regression results indicate that the commercial credit securitization rate (Ntc) has a statistically significant impact across multiple specifications. Specifically, the coefficient for Ntc is -0.0109 ($t = -1.99$) in the initial model, while subsequent models yield coefficients of 0.01685 ($t = 2.73$), 0.0138 ($t = 3.21$), and 0.1848515 ($t = 1.94$), all significant at the 5% or 10% levels as indicated by the asterisks. These models control for fixed effects (Yes/Yes) with a total sample size of 14,449 observations.

Adj. R-squared

Rating × SOE Rating ×

SOE × Post

Second, we examine the expansion of interest-free trade credit. To explore the structural changes on the liability side, we construct the trade credit securitization rate (Ntc)—defined as the ratio of notes payable to the total scale of trade credit financing—as the dependent variable. The regression results (Table 8, Column 2) show that the coefficient of the core interaction term is significantly negative at the 5% level (-0.0109). This reflects that, in the face of rising explicit credit thresholds and risk premiums, high-rating state-owned enterprises (SOEs) leverage their dominant positions in the supply chain to reduce their reliance on notes payable, which possess quasi-financial attributes and incur discounting costs.

The structural substitution of accounts payable for notes payable dilutes the average borrowing interest rate on corporate balance sheets. To some extent, this explains the relative convergence observed in debt financing costs ($Cost2$) during the micro-level correction period.

However, the sharp drop in arbitrage returns on the asset side (Rsr) and the substantial increase in credit thresholds mean that enterprises still bear a high comprehensive financial burden ($Cost1$).

The analysis of the "scissors gap" between the dynamic trends of $Cost1$ and $Cost2$ demonstrates that the policy' s effectiveness extends beyond mere "price intervention." While correcting explicit risk pricing, the policy has performed a deep-level correction of the balance sheets of high-rating SOEs that were overly dependent on financial arbitrage. This was achieved by suppressing "circular note financing" and promoting "supply chain de-financialization."

(2) Heterogeneity Analysis: The Weakening of "Too Big to Fail" Expectations

To verify Hypothesis H2 (the scale asymmetry hypothesis) proposed in this paper, we examine whether the policy effects of the "New Asset Management Regulations" exert a real impact on the "too big to fail" phenomenon and investigate the marginal impact of enterprise size on policy effectiveness.

In this study, a fourth-level interaction term—enterprise size ($Size$)—is introduced into the original benchmark regression model. We obtained a significant positive coefficient ($t = 5.93$). Based on this, we conduct a continuous moderating effect analysis using a Difference-in-Differences-in-Differences (DDD) model, primarily analyzed by plotting the marginal effects (Figure 4 [Figure 4: see original paper]).

Dependent Variable

$Cost1$ (Net Financial Expense Ratio)

Rating × SOE × Post × Size

Specific ownership trends Individual / Time fixed effects Sample size (N)

Moderating effect of firm size (Size) 0.0001*** (5.93) -0.0026*** (-5.62) Yes / Yes 14,447

Adj. R-squared

Rating × SOE × Post

The positive coefficient of the quadruple interaction term (vertical axis) implies that scale is no longer a guarantee of financing security for large-scale, high-rated enterprises; instead, it has become a factor that drives up risk pricing. For high-rated state-owned enterprises (SOEs), the larger the scale, the higher the risk compensation demanded by the market

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.