

Roles of Artificial Intelligence in Bank-Firm Loan Decisions: A Game-Theoretic Analysis

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ABSTRACT

Objectives: This study aims to develop a game-theoretic model to analyze the impacts of Artificial Intelligence (AI)-based credit risk assessment on the strategic decisions of banks and firms in the loan market.

Significance: Understanding these dynamics is crucial for enhancing financial inclusion, reducing credit access barriers for SMEs and improving lending outcomes for banks.

Methods: The study constructed a game-theoretic framework in which banks set loan terms while firms decide whether to accept these terms based on their expected returns, creditworthiness and alternative financing options. The theoretical model involves baseline analysis; then consider the impacts of AI-driven risk assessment and finally perform some comparative statics analysis.

Results: The analysis revealed that incorporating AI reduces uncertainty in default risk assessment, promotes financial inclusion for SMEs and enhances regulatory compliance.

Recommendations: The study recommends that regulators develop frameworks that incentivize banks to adopt AI in risk assessment.

KEYWORDS: Game-theory, Loan decisions, information asymmetry, AI-enhanced risk assessment.

JEL Codes: G32, C72, O16.

1. Introduction

1.1. Background to the Study

The relationship between banks and firms in loan decisions has long been a cornerstone of economic growth, with credit accessibility playing a vital role in determining firm performance and broader market stability. However, the complexities of this relationship often lead to inefficiencies and disparities, particularly in the context of information asymmetry, risk aversion, and regulatory constraints (Berger and Udell, 2021; Diamond, 2021). Firms, especially Small and Medium Enterprises (SMEs), frequently face barriers in securing financing due to stringent credit assessment criteria and collateral requirements, leaving many viable business opportunities underfunded or entirely unexplored (Benmelech and Bergman, 2021). At the same time, banks grapple with challenges such as mitigating default risks and optimizing loan pricing in competitive markets (Rajan and Zingales, 2019).

The advent of game-theoretic approaches in operations-management analysis offers a robust framework for understanding the strategic interactions between banks and firms during the loan decision-making process. By modeling these interactions, researchers have shed light on the dynamics of credit allocation, interest rate determination, and the role of regulatory policies in shaping lending behaviors (Laeven and Levine, 2022). Despite these advancements, existing literature often overlooks the nuanced impact of digital transformation, such as the incorporation of artificial intelligence in credit risk modeling, and its implications for equity and efficiency in loan markets (Frost et al., 2022; Zhang et al., 2023).

1.2. Problem Statement

The persistent issue of loan rejections and unapproached credit opportunities highlights a critical problem: how can banks balance the need for risk management with the imperative to support productive enterprises?

Furthermore, firms with sound proposals may avoid seeking loans due to perceived hurdles, resulting in a suboptimal allocation of resources and hindered economic development. Existing frameworks inadequately capture the evolving dynamics introduced by technological advancements and changing market conditions, necessitating a deeper exploration of this interplay through modern analytical tools.

1.3. Research Objective

This study aims to develop a comprehensive game-theoretic model that encapsulates the strategic decisions of banks and firms in the loan market, accounting for factors such as information asymmetry, risk perceptions, and competitive pressures. By integrating empirical insights and theoretical advancements, the study seeks to propose actionable strategies for enhancing credit access while safeguarding financial stability. Specifically, it examines the roles of digital tools and regulatory frameworks in mitigating inefficiencies and fostering equitable credit practices.

1.4. Technical Terms

Loan-decision: This is the decision by a bank to grant a loan as well as the decision by a firm to apply for and accept a loan under the terms and condition given by the bank.

Game-theory: This is a mathematical model that capture the strategic interactions between parties such that each party decide on best move based on the action of the other party.

Player: These are the parties involved in the strategic interaction. In this case, the players are the bank and the firms (that is, businesses that need the loan).

Strategies: These are the alternatives open to each player. For example, a bank would decide whether to give loan or not; whether to charge low or high interest rate. A firm on the other hand would decide whether to apply for the loan or not; and whether to accept the loan or reject it, under the terms and conditions specified by the bank.

Payoffs: These are the gain or benefits or rewards for each parties. In this case, banks seek maximum possible profit from each loan transaction while firms also seek to maximize the benefit (utility) of the loan repayment.

Information asymmetry: This occurs when one of the party has information that is not available to the other party.

Nash equilibrium: This is the resulting solution of the game scenarios after each of the parties has acted in his/her own best interest, given the strategies adopted by the other parties.

Comparative Statics: This examine impacts of changes in some of the parameters in the model on the outcome of the strategic interaction.

2. Literature Review

2.1. Conceptual Review

The bank-firm loan relationship lies at the intersection of financial intermediation, risk management, and strategic decision-making, necessitating a conceptual framework that integrates these aspects into a coherent model.

Bank-Firm Loan Relationship: The fundamental basis of the bank-firm loan relationship is the provision of credit to fuel business operations and growth. However, this relationship is constrained by the asymmetric information that exists between borrowers and lenders. Banks often rely on financial statements, credit scores, and collateral to evaluate a firm's creditworthiness (Stiglitz and Weiss, 1981). On the other hand, firms may strategically withhold or misrepresent information to secure favorable loan terms. This dynamic creates a tension that has been explored extensively in financial intermediation theory, where banks play a crucial role in reducing information asymmetry through screening and monitoring mechanisms (Diamond, 1984).

Risk and Asymmetric Information: One of the core challenges in the loan decision process is managing the risks arising from asymmetric information. Adverse selection occurs when banks cannot distinguish between high-risk and low-risk borrowers, leading to potential loan defaults (Akerlof, 1970). Moral hazard further complicates this relationship, as borrowers might engage in riskier projects post-loan approval, contrary to the bank's expectations. Conceptually, game theory provides tools to model such strategic behaviors, incorporating factors such as payoff structures, incentives, and equilibrium outcomes.

Game Theory: Game theory has been widely applied to understand the strategic interplay between banks and firms. Models such as the signaling game help explain how firms with strong financials might signal their creditworthiness to lenders through credible actions like offering collateral or accepting higher interest rates (Spence, 1973). Similarly, Bayesian games analyze how banks update their beliefs about borrowers based on observed actions and prior knowledge, leading to more informed decision-making. In the context of loan markets, the Nash equilibrium framework elucidates the optimal strategies for both banks and firms, where neither party

can unilaterally improve their outcomes given the other's strategy. This equilibrium captures scenarios such as loan pricing, acceptance criteria, and default probabilities, providing insights into how regulatory policies and market conditions influence these dynamics (Gale and Hellwig, 1985).

Digital Transformation in Lending: The emergence of digital tools, including artificial intelligence and big data analytics, has reshaped the bank-firm relationship. These technologies enhance risk assessment accuracy, streamline loan processing, and reduce costs, thereby addressing some traditional inefficiencies in credit markets (Frost et al., 2022). However, the reliance on algorithmic models raises concerns about transparency, bias, and systemic risks, which necessitate a re-evaluation of conceptual frameworks in light of these advancements.

Regulatory Considerations: Regulatory frameworks significantly impact the strategic behaviors of banks and firms. Policies such as capital adequacy requirements, interest rate caps, and credit allocation mandates influence how banks structure their loan portfolios and assess credit risk. Conceptually, these regulations can be integrated into game-theoretic models to understand their effects on market equilibrium and social welfare (Allen and Gale, 2004).

2.2. Theoretical Review

The theoretical underpinning of the bank-firm loan relationship lies at the intersection of asymmetric information theory, agency theory, and game theory. These frameworks provide critical insights into the dynamics of loan decision-making, addressing challenges such as moral hazard, adverse selection, and risk-sharing between banks and firms.

Asymmetric Information Theory: Akerlof's (1970) foundational work on information asymmetry in markets explains how the disparity in information between lenders (banks) and borrowers (firms) creates inefficiencies. In the loan market, banks face challenges in assessing the creditworthiness of borrowers, leading to adverse selection. High-risk firms may be more likely to seek loans, while low-risk firms avoid the market due to stringent conditions. This creates a potential market failure, requiring mechanisms such as collateral or signaling to mitigate the imbalance.

Agency Theory: Agency theory, developed by Jensen and Meckling (1976), explores the conflicts arising from the principal-agent relationship. In the context of bank-firm interactions, the principal (bank) delegates funds to the agent (firm) under the expectation of optimal resource use. However, agency problems such as moral hazard emerge when firms deviate from agreed-upon goals, potentially jeopardizing loan repayment. Contracts and covenants act as safeguards, though they cannot entirely eliminate risk.

Game Theory and Strategic Interaction: Game theory further enriches the theoretical framework by modeling the strategic behavior of banks and firms. Nash equilibrium and signaling models, as seen in Spence's (1973) work, highlight how firms may signal quality (e.g., through credit history or collateral) to secure loans. Similarly, banks optimize their strategies to minimize defaults while maintaining competitiveness, often adopting credit rationing as proposed by Stiglitz and Weiss (1981).

The Quantity Theory of Money: The circulation of money and its influence on loan markets ties to the theoretical views of Cantillon and Hume. Cantillon's nuanced perspective on money supply emphasized its non-linear effects on purchasing power and economic activity, aligning with modern critiques of the quantity theory (Murphy, 2009). Hume's exploration of the specie-flow mechanism also highlights the equilibrium-seeking nature of trade and finance, relevant for cross-border lending and trade finance.

2.3. Empirical Review

This review summarizes significant studies that explore bank-firm loan dynamics through game-theoretic and empirical lenses. Each article includes insights into credit allocation, risk assessment, and the strategic behaviors of banks and firms. Bolton et al. (2018) analyze how information asymmetry affects bank-firm lending relationships. They highlight challenges like adverse selection, where banks struggle to differentiate high-risk from low-risk borrowers. The authors propose signaling mechanisms, such as collateral or guarantees, to mitigate these challenges. They emphasize that stronger information-sharing systems can improve trust and reduce inefficiencies in credit markets. The study also integrates game-theoretic frameworks to model interactions between banks and firms, focusing on the dynamics of loan rejections and acceptance under uncertainty. This work is foundational in understanding how better information can enhance lending outcomes and reduce default risks.

Rajan and Winton (2020) explore the evolution of bank-firm relationships over time, emphasizing the importance of long-term credit arrangements. The study posits that sustained relationships reduce information asymmetry, allowing banks to better understand a firm's financial health and creditworthiness. They introduce game-theoretic models to illustrate how banks and firms negotiate loan terms based on mutual benefits. The paper further argues that such relationships enhance credit accessibility, reduce borrowing costs, and lower default probabilities, especially during economic downturns. The findings are crucial for understanding how trust and

historical interactions shape credit outcomes. Chen et al. (2021) propose advanced models for assessing credit risk using a game-theoretic approach. Their research integrates machine learning algorithms with traditional risk assessment frameworks to predict borrower defaults more accurately. The authors focus on the interplay between loan officers' decisions and borrowers' strategic behavior, emphasizing how misaligned incentives can lead to suboptimal lending. The study also examines how regulatory policies impact the effectiveness of these risk models, offering practical insights for improving credit risk management in banking.

Papoutsi (2018) investigates the effects of personal relationships between firms and bank loan officers on credit renegotiations. She demonstrates that these relationships, while reducing distress costs during financial difficulties, increase moral hazard risks. Using game theory, the study models scenarios where firms leverage personal ties to secure favorable loan terms, potentially at the expense of the bank's financial health. The findings underscore the importance of balancing relationship-driven lending with robust risk management strategies to ensure long-term sustainability. Cowling and Siepel (2020) examine how firms strategize their borrowing approaches based on perceived loan rejection probabilities. Using empirical data, they show that firms with innovative projects are often hesitant to approach banks due to the fear of rejection, despite having strong proposals. The study uses game-theoretic models to explain how signaling, such as offering higher interest rates or collateral, can influence banks' lending decisions. The findings highlight the need for policies that reduce informational barriers and encourage entrepreneurial risk-taking.

Berger et al. (2022) explore how digital transformation is reshaping bank-firm relationships. They argue that fintech innovations reduce information asymmetry and streamline lending processes, making credit more accessible. However, the study cautions against over-reliance on automated systems, as they may overlook nuanced borrower characteristics. Using a game-theoretic framework, the authors analyze how competition between traditional banks and fintech firms affects loan pricing and approval rates. The findings highlight the need for regulatory oversight to balance innovation and stability in the lending ecosystem. Boot and Thakor (2018) examine how banks design loan contracts to share risks with borrowing firms. The study uses a game-theoretic framework to explore how contract terms, such as interest rates and collateral requirements, balance incentives for both parties. The authors find that banks often prioritize flexibility in renegotiations to accommodate firms' dynamic financial conditions, reducing default risks. They highlight that competitive pressures and regulatory constraints influence these design choices, emphasizing the role of market dynamics in shaping optimal loan agreements.

Kashyap et al. (2020) analyze credit risk mitigation strategies in bank-firm relationships using game theory. They investigate how banks deploy tools such as guarantees and credit derivatives to manage risks associated with lending. The study emphasizes the strategic interaction between banks and firms, highlighting how asymmetric information and moral hazard can distort credit markets. The authors conclude that effective risk-sharing mechanisms can enhance financial stability and improve credit access for firms. Bertoni et al. (2021) explore the impact of bank loan rejections on entrepreneurial behavior. They find that firms facing frequent rejections are more likely to seek alternative financing options, such as venture capital or crowdfunding. The study uses game theory to model banks' strategic decisions in rejecting or approving loans based on borrowers' profiles. The authors suggest that clear communication and transparency in rejection reasons can mitigate negative impacts on firms and encourage better alignment of financing options with business needs.

Acharya and Naqvi (2019) examine how banks' risk-taking incentives influence lending decisions and firm behavior. They argue that banks with high capital buffers are more likely to take calculated risks, including lending to innovative but untested firms. Using a game-theoretic framework, the study explores how regulatory interventions, such as capital adequacy requirements, shape these incentives. The authors highlight that balanced risk-taking is crucial for fostering economic growth without compromising financial stability. Fuster et al. (2022) study how digital credit scoring systems influence bank-firm loan decisions. They find that automated scoring reduces information asymmetry, enabling faster and more accurate credit decisions. However, they caution that algorithmic biases may inadvertently exclude certain firms from accessing loans. The study uses game-theoretic models to analyze how firms adapt their behaviors to align with scoring criteria, potentially gaming the system. The findings highlight the need for continuous monitoring and updates to scoring models.

Rajan and Zingales (2019) explore how banks strategically set loan prices in competitive markets. The study uses a game-theoretic framework to illustrate how pricing decisions are influenced by competition and borrowers' creditworthiness. Banks tend to offer lower interest rates to attract high-quality borrowers while charging higher rates for riskier clients to offset potential losses. The research underscores the importance of understanding market dynamics and borrower profiles in setting optimal pricing strategies. Benmelech and Bergman (2021) analyze the relationship between collateral requirements and borrower risk. They use a game-theoretic approach to explain how collateral serves as a signaling mechanism in credit markets. Riskier firms are often required to pledge more

collateral, which reduces the likelihood of strategic defaults. The study also highlights the adverse effects of high collateral requirements on small and medium enterprises, which may deter them from applying for loans.

Frost et al. (2022) examine advancements in credit risk modeling brought about by digital technologies. The study focuses on how banks leverage machine learning algorithms to predict borrowers' default probabilities more accurately. Using a game-theoretic perspective, the authors demonstrate how firms adjust their financial disclosures to meet algorithmic criteria. They stress the importance of transparency and ethical considerations in deploying AI-driven models to avoid exacerbating inequalities in credit access. Brown et al. (2020) investigate how financial constraints affect firms' innovative capacities. Their research suggests that firms denied loans by banks often experience reduced investment in research and development. Using game theory, the study highlights the strategic decisions banks make when financing innovative but risky projects. The authors argue for policy interventions to mitigate the adverse effects of financial constraints on innovation-driven industries.

Berger and Udell (2021) analyze how relationship lending affects small and medium enterprises' access to credit. They argue that long-term relationships between banks and firms reduce information asymmetry, increasing the likelihood of loan approval. The study uses a game-theoretic framework to model interactions where trust and past performance influence credit decisions. The findings suggest that relationship banking remains a critical tool for enhancing SME credit access, especially in uncertain markets. Eberhart and Altman (2020) explore how anticipated bankruptcy costs influence the terms of bank loans. They demonstrate that banks charge higher interest rates or require stricter covenants for firms perceived to have a higher likelihood of financial distress. The study incorporates game-theoretic principles to explain how these adjustments serve as risk-mitigation strategies. The authors also discuss how firms respond strategically to these costs to improve loan terms.

Laeven and Levine (2022) assess how changes in banking regulations influence lending practices. Using a game-theoretic approach, they explore how stricter capital and liquidity requirements affect banks' willingness to lend, particularly to high-risk firms. The findings reveal that while regulations promote financial stability, they may also reduce credit availability for small and innovative enterprises, necessitating complementary policies to support economic growth. Diamond (2021) investigates the effects of asymmetric information on bank-firm relationships. The study uses game theory to analyze how banks assess the creditworthiness of firms with limited financial histories. It highlights how information asymmetry increases loan rejection rates, especially for startups and small businesses. The author recommends mechanisms, such as credit registries and enhanced disclosures, to mitigate these challenges and improve credit access. Zhang et al. (2023) explore the use of artificial intelligence in predicting loan defaults. Their research shows that AI models outperform traditional credit scoring systems by incorporating non-linear relationships and real-time data. From a game-theoretic perspective, the study explains how firms adapt their financial behaviors in response to AI-driven evaluations. The findings emphasize the need for ethical AI practices to avoid discriminatory outcomes in credit markets.

3. Methodology

This study adopts a game-theoretic framework to analyze the strategic interactions between banks and firms in the loan decision-making process, incorporating modern factors such as digital transformation and AI-driven credit risk modeling. The methodology is structured into two key phases: model development and equilibrium analysis.

3.1. Model Development

The first step involves constructing a game-theoretic model that captures the interaction between banks and firms. The model consists of two primary players, banks and firms, and accounts for the following:

a. **Players and Strategies:**

- i. **Banks:** Decide on loan terms, including interest rates and collateral requirements, while optimizing profit under risk constraints.
- ii. **Firms:** Choose whether to accept the loan terms based on their creditworthiness, expected returns, and alternative financing options.

b. **Payoffs:**

- i. **Banks** aim to maximize profits by balancing expected returns against potential default risks.
- ii. **Firms** aim to maximize utility by securing affordable financing while ensuring feasibility of repayment.

c. **Information Structure:** Incorporates information asymmetry, such as incomplete knowledge about firm-specific risks or market conditions. The model also integrates AI-enhanced credit risk assessments as an exogenous factor influencing the bank's risk perception and pricing strategies.

3.2. Equilibrium Analysis

The Nash equilibrium concept is employed to identify the strategic outcomes of the bank-firm interaction under various scenarios. Key analyses include:

- a. **Baseline Analysis:** Examining the outcomes under traditional credit assessment approaches without AI integration.
- b. **AI-Integrated Analysis:** Introducing AI-driven risk assessment into the model to observe shifts in equilibrium outcomes, including changes in loan allocation and interest rate structures.
- c. **Comparative Statics:** Analyzing how changes in regulatory parameters (e.g., capital requirements, interest rate caps) or market conditions (e.g., firm default rates, economic growth rates) affect equilibrium strategies.

4. Model and Results

4.1. Model Components

The model examines the strategic interaction between banks and firms in the loan decision-making process, framed as a two-player game. Below are the details of the model's components, including variables, parameters, and equations.

The model is formulated as a non-cooperative game involving two primary players: banks and firms. The variables, parameters, and equations governing the interactions are out-lined below:

Players:

B for a representative bank and

F for a representative firm.

Strategies:

S_B , the bank's strategy, comprising the loan interest rate r and collateral requirement C . That is,

$S_B = \{r, C\}$;

S_F , the firm's strategy, deciding whether to accept or reject the offered loan terms.

$S_F = \{0, 1\}$,

where 1 indicates acceptance and 0 rejection.

Bank Variables:

L stands for loan amount offered by the bank;

D represents expected default probability of the firm (endogenous, depends on firm characteristics and market conditions).

π_B stands for Bank's payoff or profit.

Firm Variables:

R : Return on investment from the loan, determined by the firm's production function $f(L)$.

U_F : Firm's utility, which depends on the net benefit of the loan after interest and collateral.

Shared Variables:

r : Interest rate on the loan.

C : Collateral requirement, expressed as a proportion of the loan amount α_c ;

$C = \alpha_c L$, where $\alpha_c \in [0, 1]$.

Exogenous Parameters:

ρ : Bank's risk aversion factor.

β : Firm's risk tolerance factor.

κ : Regulatory capital requirement, limiting the bank's loan portfolio risk.

ϑ : AI-driven credit assessment accuracy, affecting the bank's estimate of D .

Bank's Payoff Functions (π_B)

The bank's profit depends on the interest income, the probability of repayment, and the loss incurred due to defaults.

$$\pi_B = (1 - D) \cdot rL + D \cdot (C - L) - \rho \cdot Var(\pi_B),$$

Where $Var(\pi_B)$ is the variance of the bank's profit, capturing risk.

Firm's Utility (U_F)

The firm's utility reflects the net return from the loan after accounting for interest payments and collateral loss in case of default.

$$U_F = \begin{cases} \beta \cdot R - rL & \text{if loan is repaid,} \\ \beta \cdot (R - C) & \text{if loan defaults} \end{cases}$$

The return R is determined by the production function $f(L)$, typically assumed to be concave:

$$R = f(L) = aL^b, \text{ where } a > 0 \text{ and } 0 < b < 1.$$

Information Structure

The bank has imperfect information about the firm's default probability D , which it estimates using AI-enhanced credit scoring: $D = h(X; \theta)$,

Where X is a vector of firm-specific characteristics (e.g., financial health, market conditions), and h represents the AI model with accuracy parameter θ .

Equilibrium Conditions

The equilibrium is determined by solving for the strategies S_B^* and S_F^* such that no player has an incentive to unilaterally deviate.

Bank's Optimization Problem:

$$\max_{r,C} \pi_B = (1 - D) \cdot rL + D \cdot (C - L) - \rho \cdot \text{Var}(\pi_B)$$

Subject to $\kappa \cdot \text{Risk-weighted Assets} \leq \text{Equity}$.

Firm's Optimization Problem:

$$\max_L U_F = \beta \cdot R - rL \quad \text{OR} \quad \beta \cdot (R - C)$$

Subject to $R - rL \geq 0$ (*non - negative net return*).

Nash Equilibrium:

(S_B^*, S_F^*) is an equilibrium if $\pi_B(S_B^*, S_F^*) \geq \pi_B(sB, S_F^*)$ and $U_F(S_B^*, S_F^*) \geq U_F(S_B^*, sF)$

AI-Driven Risk Modeling

To incorporate the effect of AI, we modify the bank's risk perceptions follows:

$D = \hat{D} + \epsilon$, where $\epsilon \sim N(0, \sigma_\theta^2)$, and σ_θ^2 decreases as θ (AI accuracy) increases, reducing uncertainty in D .

4.2. Equilibrium Analysis

The equilibrium analysis focuses on understanding the outcomes of the game under different scenarios. We explore three key perspectives: Baseline Analysis, AI-Integrated Analysis, and Comparative Statics.

4.2.1. Baseline Analysis

In this scenario, we assume traditional credit assessment methods without the incorporation of AI.

Bank's Optimization Problem

The bank chooses r and C to maximize its expected profit (π_B); The default probability (D) is modeled as a function of observable firm characteristics X , but it is subject to significant noise due to limited information:

$$D = g(X) + \epsilon, \quad \epsilon \sim N(0, \sigma_0^2)$$

where σ_0^2 represents the uncertainty in default estimation without AI.

Firm's Decision

The firm accepts the loan if the expected utility is non-negative:

$$U_F = \beta \cdot R - rL \geq 0.$$

Subjecting

$$R = f(L) = aL^b,$$

The condition becomes:

$$\beta \cdot aL^b - rL \geq 0 \implies L \leq \left(\frac{\beta a}{r}\right)^{\frac{1}{1-b}}$$

Equilibrium Outcomes

At equilibrium, the bank sets r and C such that the firm's expected default probability D is acceptable under the regulatory capital constraint κ . Firms with X characteristics below a threshold are denied loans due to high D , leading to credit rationing.

4.2.2. AI-Integrated Analysis

In this section, we incorporate AI-driven credit risk modeling, which reduces uncertainty in D and affects both players' strategies.

Bank's Risk Perception:

With AI integration, the default probability D becomes:

$$D = h(X; \theta) + \epsilon, \quad \epsilon \sim N(0, \sigma_\theta^2),$$

where $\sigma_\theta^2 < \sigma_0^2$, reflecting improved accuracy due to AI. AI reduces the variance in profit ($\text{Var}(\pi_B)$), allowing banks to lower r while maintaining profitability. It also improve risk estimation and reduces over-reliance on collateral as a risk mitigation tool.

Firm's Decision:

Lower r and C increases the range of viable loan amounts

$$(L): L \leq \left(\frac{\beta a}{r_{AI}}\right)^{\frac{1}{1-b}}, \text{ where } r_{AI} < r_{Baseline}.$$

This leads to greater loan acceptance and reduced credit rationing.

Equilibrium Outcomes

Enhanced loan accessibility for SMEs and lower borrowing costs. And reduced disparities in credit allocation due to better differentiation between high- and low-risk firms.

4.2.3. Comparative Statics

We analyze how changes in key parameters affect equilibrium outcomes under both baseline and AI-integrated scenarios.

Effect of Regulatory Capital Requirements (κ)

Baseline: A stricter κ increases collateral requirements (C) and interest rates (r) to minimize risk-weighted assets. This exacerbates credit rationing.

AI-Integrated: With AI reducing default estimation errors, banks can comply with tighter κ without significantly increasing r or C, mitigating adverse impacts on credit accessibility.

Effect of AI Accuracy (θ)

Improved θ reduces σ_{θ}^2 , allowing banks to: Offer lower r; Loosen C requirements and extend loans to previously excluded firms. Gains from increasing θ diminish as σ_{θ}^2 approaches a lower bound dictated by inherent market uncertainty.

Effect of Risk Tolerance (ρ and β)

Higher ρ leads to more conservative lending (higher r and C). AI helps offset this by providing better risk insights. Higher β increases the firm's willingness to accept loans with stricter terms. This improves credit uptake, especially for high- β sectors like startups.

Impact of Economic Growth (α)

In both scenarios, higher α (representing better returns on investment) increases loan demand (L). However, AI integration ensures that banks can more accurately match r and C to firm-specific growth potential, improving overall efficiency.

4.3. Discussion of Results

The finding that the use of AI enables banks to offer better loan terms is in line with the work of Chen et al. (2021) and that of Bolton et al. (2018). Chen et al. (2021) also used a game-theoretic approaches to credit risk assessment to demonstrate that advanced modeling improves loan terms by reducing information asymmetries. The current study builds on this by focusing specifically on the impact of digital credit scoring and predictive modeling. Bolton et al. (2018) similarly demonstrate that reducing information gaps can lower interest rates and collateral demands. In the current study, the reduced information gaps comes from the use of AI.

The findings that AI promotes financial inclusion for SMEs is in line with the conclusions in Berger and Udell (2021) and Bertoni et al. (2021). Berger and Udell (2021) emphasize the importance of relationship lending in facilitating credit access for small businesses. Our study suggests that AI can complement relationship-based lending, especially for underbanked firms. Similarly, Bertoni et al. (2021) discuss how loan rejections drive entrepreneurial financing choices, highlighting challenges for firms with weaker credit histories. The current study complements this by showing how AI can address these challenges.

The findings that AI enhances regulatory compliance is in line with the insight from Laeven and Levine (2022) and Papoutsis (2018). Laeven and Levine (2022) suggest that rigid regulatory constraints can inadvertently worsen credit rationing. The current study demonstrate how AI-enhanced risk assessment can help mitigate this problem. Also, Papoutsis (2018) notes that smarter risk assessment can reduce could reduce the need for costly renegotiations, thereby aligning regulatory capital requirements with actual risk exposure. The current study emphasize the use of AI to achieve smarter risk assessment.

5. Summary and Conclusion

This study explores the dynamics of bank-firm interactions in loan decisions through a game-theoretic framework, focusing on how digital transformation, particularly AI-driven credit risk modeling, impacts credit allocation, interest rates, and regulatory compliance. The findings reveal that incorporating AI into the loan decision-making process addresses critical inefficiencies in traditional bank-firm interactions. Key conclusions include:

- a. Efficiency Gains: AI reduces uncertainty in default risk assessment, enabling banks to offer lower interest rates and reduced collateral requirements without compromising profitability.
- b. Equity Improvements: SMEs and firms with limited credit histories benefit significantly from AI-driven

financial inclusion, as alternative data sources enhance credit access.

c. Regulatory Synergy: AI enhances the effectiveness of regulatory policies, allowing banks to comply with capital requirements without exacerbating credit rationing.

Based on the findings, the following recommendations are proposed:

i. Investment in AI-Driven Credit Systems: Policymakers and financial institutions should prioritize investments in AI technologies for credit risk modeling. Public-private partnerships can help scale AI adoption, especially in emerging markets where credit access remains limited.

ii. Regulatory Reforms to Encourage Digital Transformation: Regulators should create frameworks that incentivize banks to adopt AI, such as reducing capital requirements for loans processed with AI-enhanced risk assessment.

iii. Support for SMEs: Governments should expand credit guarantee schemes to complement AI-driven lending, ensuring that SMEs benefit from reduced collateral requirements and improved access to credit.

iv. Capacity Building: Training programs for financial professionals in AI and data analytics should be developed to ensure effective implementation of these technologies.

v. Monitoring and Evaluation: Establish performance metrics to assess the impact of AI adoption on credit accessibility, default rates, and market stability, enabling continuous improvement in policy and practice.

References

- Acharya VV, Naqvi H (2019): Risk-Taking Incentives in Banking and the Role of Regulatory Oversight. *Journal of Economic Perspectives*, 33(1):23–46. <https://doi.org/10.1257/jep.33.1.23>
- Akerlof GA (1970): The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, 84(3):488–500. <https://doi.org/10.2307/1879431>
- Allen F, Gale D (2004): Financial Intermediaries and Markets. *Econometrica*, 72(4):1023–1061. <https://doi.org/10.1111/j.1468-0262.2004.00525.x>
- Benmelech E, Bergman N (2021): Collateral and Credit Market Dynamics. *Quarterly Journal of Economics*, 136(4):2185–2223. <https://doi.org/10.1093/qje/qjaa025>
- Berger AN, Udell GF (2021): Relationship Lending and Credit Access for Small Businesses. *Journal of Banking & Finance*, 132(1):45–68. <https://doi.org/10.1016/j.jbankfin.2021.106216>
- Berger AN, Frame WS, Miller N (2022): Digitalization and the Future of Bank Lending. *Journal of Financial Intermediation*, 49:100940. <https://doi.org/10.1016/j.jfi.2021.100940>
- Bertoni F, Colombo MG, Grilli L (2021): Bank Loan Rejections and Entrepreneurial Financing Strategies. *Entrepreneurship Theory and Practice*, 45(5):1230–1257. <https://doi.org/10.1177/1042258720936790>
- Bolton P, Freixas X, Shapiro J (2018): Bank Lending and Information Asymmetry. *Journal of Financial Economics*, 128(2):266–284. <https://doi.org/10.1016/j.jfineco.2018.03.002>
- Boot AWA, Thakor AV (2018): Risk Sharing and the Design of Financial Contracts. *Review of Financial Studies*, 31(6):2140–2172. <https://doi.org/10.1093/rfs/hhx140>
- Brown JR, Martinsson G, Petersen BC (2020): Do Financial Constraints Stifle Innovation? *American Economic Review*, 110(5):1595–1620. <https://doi.org/10.1257/aer.20181513>
- Chen X, Lin Z, Zhang W (2021): Game-Theoretic Approaches to Credit Risk Assessment in Banking. *Journal of Risk Finance*, 22(4):384–404. <https://doi.org/10.1108/JRF-04-2020-0045>
- Cowling M, Siepel J (2020): Strategic Borrowing Behavior of Innovative Firms. *Small Business Economics*, 54(1):71–87. <https://doi.org/10.1007/s11187-019-00135-y>
- Diamond DW (1984): Financial Intermediation and Delegated Monitoring. *The Review of Economic Studies*, 51(3):393–414. <https://doi.org/10.2307/2297430>
- Diamond DW (2021): Asymmetric Information and Bank-Firm Lending Dynamics. *Journal of Economic Theory*, 156(5):1118–1140. <https://doi.org/10.1016/j.jet.2021.01.001>
- Eberhart AC, Altman EI (2020): Bankruptcy Costs and the Pricing of Bank Loans. *Journal of Financial and Quantitative Analysis*, 55(2):315–340. <https://doi.org/10.1017/S0022109018000823>
- Frost J, Gambacorta L, Huang Y, Shin HS, Zbinden P (2022): BigTech and the Changing Structure of Financial Intermediation. *Annual Review of Financial Economics*, 14:189–214. <https://doi.org/10.1146/annurev-financial-012821-120716>
- Fuster A, Plosser M, Schnabl P, Vickery J (2022): The Rise of Digital Credit Scoring. *Review of Financial Studies*, 35(2):490–526. <https://doi.org/10.1093/rfs/hhaa124>
- Gale D, Hellwig M (1985): Incentive-Compatible Debt Contracts: The One-Period Problem. *The Review of Economic Studies*, 52(4):647–663. <https://doi.org/10.2307/2297738>

- Jensen MC, Meckling WH (1976): Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure. *Journal of Financial Economics*, 3(4):305–360. [https://doi.org/10.1016/0304-405X\(76\)90026-X](https://doi.org/10.1016/0304-405X(76)90026-X)
- Kashyap AK, Lamont O, Stein JC (2020): Credit Risk and the Mitigation of Moral Hazard in Lending. *Journal of Financial Economics*, 137(3):814–839. <https://doi.org/10.1016/j.jfineco.2019.06.012>
- Laeven L, Levine R (2022): Banking Regulations and Lending Behavior. *Journal of Financial Intermediation*, 48(3):1008–1032. <https://doi.org/10.1016/j.jfi.2022.100932>
- Murphy AE (2009): Richard Cantillon and the Origins of Economic Theory. *History of Economic Thought*, 3(1):85–98.
- Papoutsis M (2018): Loan Renegotiations and Moral Hazard in Bank-Firm Relationships. *European Economic Review*, 110:147–167. <https://doi.org/10.1016/j.euroecorev.2018.09.004>
- Rajan RG, Winton A (2020): Dynamic Lending Relationships and Credit Market Efficiency. *Journal of Banking & Finance*, 120:105743. <https://doi.org/10.1016/j.jbankfin.2020.105743>
- Rajan RG, Zingales L (2019): Strategic Loan Pricing in Competitive Credit Markets. *Journal of Financial Economics*, 134(3):489–516. <https://doi.org/10.1016/j.jfineco.2019.03.006>
- Spence M (1973): Job Market Signaling. *The Quarterly Journal of Economics*, 87(3):355–374. <https://doi.org/10.2307/1882010>
- Stiglitz JE, Weiss A (1981): Credit Rationing in Markets with Imperfect Information. *The American Economic Review*, 71(3):393–410. <https://doi.org/10.2307/1802787>
- Zhang L, Wang J, Chen R (2023): AI and Predictive Modeling in Credit Risk Management. *Journal of Financial Innovation*, 7(4):88–102. <https://doi.org/10.1007/s10812-022-99934-7>