Artificial Intelligence Driven Responsible Green Finance: Banks' AI Adoption, Corporate Environmental Information Manipulation, and Loan Contract

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Conflict of Interest

The authors declare that they have no conflict of interest.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process: During the preparation of this work the authors did not use AI and AI-assisted technologies.

Abstract

Green credit is intended to support firms with truly environmental potential, but the widespread manipulation of environmental information by firms undermines its effectiveness and hinders progress toward sustainable development goals. This study investigates whether the adoption of artificial intelligence (AI) by banks can address this issue. Using a dataset of 1,209 loan contracts issued in China between 2019 and 2023, which is one of the largest polluters and green finance implementors, we find that banks adopting AI impose significantly higher interest spreads on firms exhibiting signs of environmental information manipulation. The effect is more prominent for loan contracts granted by green-experienced banks and those to non-polluting firms. Our analysis identifies two underlying mechanisms: AI enhances banks' capabilities for both risk identification and legitimacy. These findings offer novel insights into the role of technological advancement in green credit practices and contribute to the growing literature at the intersection of finance, sustainability, and digital transformation.

Keywords: Artificial intelligence; Green credit; Environmental information; Manipulation, Loan contract

1 Introduction

With growing concerns over environmental degradation, many countries have introduced green credit policies to integrate environmental responsibility into financial decision-making (Ahlström and Monciardini, 2022; Hrazdil et al., 2023). Green credit refers to the incorporation of a firm's environmental performance into the criteria used by banks when issuing loans, with the aim of aligning financial incentives with environmental sustainability (Edmans and Kacperczyk, 2022; Stroebel and Wurgler, 2021). However, green credit has been criticized for its vulnerability to manipulation, as firms may present superficially compliant or misleading environmental disclosures to secure favourable loan terms, namely, environmental information manipulation (Cumming et al., 2016; Flammer, 2021; Zhang, 2022). Such practices distort the intent of green credit and contribute to so-called "anti-environmentalism," raising concerns that environmental and economic goals are inherently difficult to reconcile (Babiker et al., 2003; Marquis et al., 2016; Parguel et al., 2011). Addressing how to curb these misrepresentations is therefore crucial for firms, banks, and financial systems.

A primary strategy to counter environmental information manipulation is to enhance the efficiency and accuracy of banks' information collection and verification processes (Ahlström and Monciardini, 2022; Bothello et al., 2023; Crilly et al., 2016), which has long been a challenge (Bolton and Freixas, 2000; Myers and Majluf, 1984). However, the rise of emerging technologies, particularly artificial intelligence (AI), offers new opportunities to address these issues (Aman et al., 2024; Bauer et al., 2023). As one of the most advanced information technologies, AI's application scenarios are various, in which bank business is typical because it is information-sensitive and can be standardized efficiency improved by AI (Rammer et al., 2022). Reflecting this, we explore the central question: *Whether a bank's adoption of AI can mitigate the effect of* *corporate environmental information manipulation on preferential loan contracts?*

However, the literature remains scant on the role of AI in the relationship between corporate environmental information manipulation and loan financing. While many studies highlight that green credit relies heavily on rich environmental information from loan applicants (Homar and Cvelbar, 2021), they also acknowledge that such information is more prone to manipulation than traditional financial data. Existing research confirms that environmental information manipulation adversely affects the performance and credibility of green credit schemes (Doumpos et al., 2023; Rahman et al., 2023). Nevertheless, most studies examine the financial effects of AI and environmental disclosures separately (Doumpos et al. 2023; Xing et al. 2021; Zhang 2022), offering limited insight into how AI might directly mitigate environmental information manipulation.

In theory, AI can establish standardized, automated procedures for reviewing corporate environmental disclosures (Doumpos et al., 2023; Rahman et al., 2023) , thereby reducing asymmetries in environmental information. Moreover, AI can enhance the quality of decision-making in situations where environmental data manipulation is prevalent (Rammer et al., 2022). Based on this perspective, we propose two mechanisms through which AI can address this issue. First, AI improves banks' risk identification capabilities, enabling them to detect manipulated environmental information and issue more appropriate loan contracts. Second, AI enhances the legitimacy of banks' decision-making by reducing human interference in the loan approval process. Banks with higher level of legitimacy will be more cautious and sensitive to firms' engagement in environmental information manipulation. Therefore, the efficiency and fairness of loan pricing will be further strengthened.

We use loan-contract level data to answer the above research question and potential channels. Our sample contains 1209 loan contracts for listed firms in China from 2019 to 2023, which is one of the largest green credit implementers and polluters. We especially focus on firms' environmental reports, which are the main source of environmental information. We measured the degree of environmental information manipulation using an insightful method, naïve Bayesian machine learning approach, as described by Li (2010) and Xing et al. (2024). Banks' AI application data are manually collected from banks' annual reports. We analyse the attributes of AI and its effect in combination noting the effect of information asymmetry (Heimstädt, 2017; Lyon and Montgomery, 2013). Our baseline results confirm that banks' AI adoption can mitigate corporate use of environmental information manipulation to obtain lower loan interest rates. We utilize several methods, such as instrumental variables and entropy matching, for robustness testing. Meanwhile, as the effects of AI may vary in different firms and banks, we discuss heterogeneities. We also test the dual proposition that banks' risk identification capabilities and legitimacy are improved by AI. The findings confirm that AI is effective in exposing unrealistic claims about use of green credit, and are instructive for banks, regulators and firms.

This paper has three contributions to the literature. First, we contribute to the literature that discusses how technological change affects the development of green credit by exploring the effect of AI. Digitalization is rapidly adopted by many firms. Previous research finds that the impacts of digitalization are generally positive. For instance, it can improve corporate information transparency (Che et al., 2023), productivity (Gaglio et al., 2022), and financial performance (Bresciani et al., 2021). As one of the most advanced digital technologies, AI is theoretically more powerful in information review activities. This is especially useful for banks because conventional financing procedures require much analysis of data, which needs human input to check and review (Demiroglu and James, 2010). Nevertheless, although AI and digital systems are increasingly used by the finance sector, their adoption and the consequences of doing so are less explored (Wang et al., 2024a). To our knowledge, we are the first to discuss the effects of AI on loan financing by connecting it with corporate environmental information manipulation. From an economic perspective, our findings provide original evidence on the nexus between technological change, green credit, and sustainable development.

Second, we relate environmental information manipulation and green credit to the theory of information asymmetry. Green credit has been widely discussed and practiced in academia and industry. Plenty of studies analyse its attributes, effects, and driving factors (Ahlström and Monciardini, 2022; Edmans and Kacperczyk, 2022; Wu and Shen, 2013). Nevertheless, some recent literature indicates that green credit may not achieve green objectives (Zhang, 2022). This problem is found in both developing and developed markets (Stroebel and Wurgler, 2021). Misleading information about green credit can have disruptive effects on confidence in green credit. Our paper proposes a framework for dealing with misinformation on green credit and addresses this using emerging technologies such as AI. Therefore, as we discuss a solution to the use of environmental information manipulation for green credit, our findings are insightful for regulatory policies and banks' strategies, helping to restoring confidence in green credit.

Finally, we also contribute to the literature on technological governance relating to corporate greenwashing behaviours and environmental information manipulation. Many studies discuss the specification, proxy, and consequences of greenwashing, especially in firms (Bothello et al., 2023; Crilly et al., 2016; Du, 2015; Marquis et al., 2016; Parguel et al., 2011; Walker and Wan, 2012; Zhang, 2022). A consensus is that environmental information manipulation is harmful to positive environmental development and should be resisted by firms' stakeholders. However, some literature finds that environmental information manipulation can improve corporate environmental evaluation, financial benefits, and financing resources because such information is hard to identify (Guo et al., 2017; Lee and Raschke, 2023; Li et al., 2023). Following the call for methods for controlling corporate environmental information manipulation (Xing et al., 2021; Zhang, 2022), we propose that AI can play a crucial role. Our main findings show that AI mitigates information manipulation on green credit, reflecting AI's capabilities at detecting and correcting information manipulation. Our heterogeneity and channel tests provide additional evidence. Such comprehensive discussions are beneficial for the healthy environmental development.

2 Background, Literature, and Hypothesis

2.1 Literature on Green Credit and Environmental Information Manipulation

The development of green credit policies and practices has stimulated research on its economic and environmental consequences. For instance, Edmans and Kacperczyk (2021) conclude that green credit has significantly changed the attitudes of firms and their stakeholders. Flammer (2021) finds that green credit are more popular than conventional credit in the US and help to cultivate corporate environmental performance. Similarly, in China, literature confirms that the costs and difficulty of acquiring loan contracts of polluting firms and projects have increased since the green credit policy was implemented (Xing et al., 2021). The consensus of these studies is that green credit plays a positive role in firms and financial markets.

However, emerging literature finds evidence of the "dark side" of green credit.

Ahlström and Monciardini (2022) suggest that green credit participants (firms, banks and other organizations) may contest the relative policies. Benlemlih and Yavaş (2023) demonstrate that changing climate policies (including green credit policies) cannot achieve the aim of firms' environmental protection. Based on these, green credit may lead to opportunistic corporate environmental behaviours. For instance, Xing et al. (2021) suggest that green credit in China aggravates the conflict between firms and banks. Firms may use more symbolic and myopic behaviours to cater to banks. This is further supported by Zhang (2022), who shows that China's green credit significantly increases corporate greenwashing.

More importantly, greenwashing behaviours can affect the implementation of green credit, resulting in the positive relationship between environmental information manipulation and loan financing in the context of green credit. Theoretically, the principal responsibility of green credit is allocating financing resources to truly green fields (Edmans and Kacperczyk, 2022). Thus, loan contracts granted to firms with environmental information manipulation can be defined as the phenomenon that resources are misallocated (Cumming et al., 2016; Hrazdil et al., 2023; Managi et al., 2022). Plenty of studies indicate the existence of this problem. For example, Bothello et al. (2023) suggest that large firms can use environmental information manipulation to acquire more financial and market resources and can more easily avoid negative stakeholder perceptions. Similarly, Xing et al. (2024) find that China's firms with greater degrees of environmental information manipulation have more investment activities in green credit, because the information helps them receive more financing resources and firms use such investment to disguise the environmental information manipulation. Attig et al. (2021) directly test the positive relationship between environmental information manipulation and loan financing. Cao et al. (2022) and Liu et al. (2024) use data on China's green credit and confirm that firms with environmental information manipulation obtain better loan contract conditions.

Another group of studies explores the governance of environmental information manipulation. First, appropriate external supervision and regulation can prevent firms from adopting environmental information manipulation. Liu et al. (2024) suggest that collaborative regulation, through formal institutions, can control corporate environmental information manipulation behaviours. Du (2015) finds that media, as an informal supervision mechanism, also plays a governance role in corporate environmental information manipulation. The crucial rationale of such governance is the information mechanism. Only when the environmental information manipulation of firms is detected by regulators or the public, can regulations or media coverage be effective in warning firms. Second, reducing information asymmetry between banks and firms can mitigate the impact of environmental information manipulation. Xing et al. (2021) indicate that banks may be confused by environmental information manipulation. We can thus infer that more concrete information supporting substantial positive corporate environmental performance helps banks make rational decisions. Nevertheless, investigating environmental information manipulation is still challenging because banks cannot directly control corporate disclosure and the instrument for measuring environmental information manipulation is also limited (Hrazdil et al., 2023; Wu and Shen, 2013). Stemming from such difficulties, searching for instruments that can provide more information is beneficial.

2.2 Literature on AI Adoption

The needs for more efficiency methods for detecting environmental information manipulation is associated with the emerging literature on technological change, especially on the field of artificial intelligence (AI). The emergence of AI stems from digitalization. AI is based on big data and deep learning algorithms, which can identify and validate complex data and information (Aman et al., 2024; Bauer et al., 2023). The computational power of digital systems has soared in recent years, leading to computers imitating human thinking and assisting individuals to make decisions (Rammer et al., 2022). From the technology perspective, AI has significant characteristics of systematization, standardization, and automation (Babina et al., 2024). From the organization perspective, the primary function of AI is acceleration in efficiency. For instance, Mishra et al. (2022) suggest that AI improves corporate operating efficiency. Similarly, Babina et al. (2024) find that AI is beneficial for corporate growth. They indicate that AI strengthens the capability of information production, transmission and utilization. As a result, the adoption of AI significantly changes firms' business patterns, including areas such as innovation, marketing, and supply chain management (Benzidia et al., 2021). This is because AI improves capacity to exploit data which are useful to cultivate innovation (Igna and Venturini, 2023). Furthermore, recent literature connects AI with corporate sustainability and positive outcomes. For example, Chotia et al. (2024) insert AI into the framework of a corporate sustainable business model, and find that AI is useful to achieve carbon neutrality. Wang et al. (2024b) confirm that better green innovation performance can be driven by AI.

The characteristics of AI are helpful to supplement information from two aspects, i.e., standardization and automation. First, standardization means that AI can transform complicated information to a systematic form (Cantero Gamito, 2023). The core of AI is algorithms built on a huge volume of existing knowledge, which can analyse different types of information by mathematical methods and summarise them in a unified framework. For instance, corporate environmental information is usually considered as non-standard since firms can disclose it according to their preferences and habits[1]. This is because environmental disclosure uses textual information rather than numerical values. Nevertheless, AI's algorithms can quantify textual information after they are trained using environmental knowledge. An important implication of AI's quantification is determining information's attributes, e.g., good or bad information.

Second, automation can solve the low-efficiency problem of information acquisition and analysis by excluding human interference. AI's automation refers to AI's ability to automatically accomplish or support tasks such as information collection, data recruitment, and programmatic analysis (Yu et al., 2024). In conventional methods, human need complex capabilities to analyse it, such as hiring professionals in the field of environmental management, even if they collect adequate information. These are costly and time-consuming. More importantly, compared to automatic analysis of AI, manual analysis suffers higher failure rates further reducing the efficiency of analysis. AI is able to provide more timely and accurate analysis on information.

In summary, some emerging literature has focused on the "green" function of AI. However, the exploration of green credit is scant. Limited research has shed light on the adoption of AI in banking sector. Previous literature mainly focuses on the general effects of AI in firms. Banks, as some of the most important information users in a market, pay more attention to the informational capabilities of AI. The studies referred to above support the view that AI can uncover more data and information to mitigate the impact of environmental information manipulation on loan contract conditions. Therefore, we also fill the research gap by discussing the characteristics of AI and its effects on green credit.

[1] Although some disclosure standards have been published such as GRI standard, the degree of standardization of environmental disclosure is still lower than that of financial statements.

2.3 Hypothesis Development

The relationship between banks' AI adoption, corporate environmental information manipulation, and loan contract is related to information asymmetry theory, which suggests that individuals and organizations with advantaged information can acquire abnormal benefits, but such information asymmetry also exaggerates market friction (Birindelli et al., 2024; Wu and Shen, 2013). Environmental information manipulation is a representative embodiment of advantaged information. Firms with environmental information manipulation not only cater to environmental regulations and acquire institutional benefits (Li et al., 2023), but also confuse banks' judgement when firms apply for loans. We suggest that environmental information manipulation incurs two problems. On the one hand, banks may make risky decisions (Xing et al., 2021). They may consider that such environmental information manipulation is concrete performance and beneficial for firms. This will trigger higher solvency risks to banks (Aintablian et al., 2007; Wu et al., 2023). On the other hand, banks may face more legitimacy problem (Zhang, 2022). When firms' environmental information manipulation is detected by regulators, banks may also be punished because they are regarded as supporters of these firms (Finger et al., 2018). Therefore, the problem of preferential loans granted to firms with environmental information manipulation can be solved only when banks can mitigate environmental information asymmetry. In this case, AI can play a significant role.

First, banks adopting AI can better illustrate firms' environmental image as all environmental information (whether text, numerical or graphical) can be quantified into standardized forms by AI. Thus, banks have better capabilities of risk identification. Banks are more able to identify which information may be manipulated and increase risks. They can make more rational decisions for hedging solvency risks and mitigating future financial impacts. Specifically, banks can charge higher interest spreads for suspected firms' environmental information manipulation when they grant loans. Besides, the automation underpinning AI leads conclusions from the analysis to be more stable and accurate (Aintablian et al., 2007; Wu et al., 2023). Accordingly, the adoption of AI can simultaneously achieve the aims of rapid review and risk control.

Second, AI builds a foundation to automatically match corporate information with regulations and policies, improving banks legitimacy. Legitimacy friction between green credit practices and regulations exists because banks have more human interference. For instance, bank managers may be willing to grant loans to firms with environmental information manipulation due to their performance pressure(Zhang, 2022). However, AI systems of banks, by standardization, can decide whether firms' environmental activities are in line with the current regulations and policies. Mature AI systems and large models are also trained to learn governmental policies by APIs (Application Programming Interfaces) which are widely provided by many organizations and Internet service firms[2]. In combination with standardized information, environmental information manipulation will be considered as a contradiction. As the consequence, banks with greater legitimacy and without human interference are more cautious and sensitive to corporate environmental information manipulation, and will not grant preferential loans to such firms (Granja and Leuz, 2024).

Above all, we suggest that AI can improve risk identification capability and legitimacy of banks, and help them better detect environmental information manipulation. Therefore, banks with AI adoption can make rational financing decisions to correct the use of manipulated information in acquiring preferential loan contracts. Accordingly, we propose the following hypothesis:

[2] For example, Baidu (a leading Internet firm of searching service in China) focuses on AI products from 2021, providing related services to individuals and organizations.

H1: Compared to banks without AI adoption, loan contracts for firms with the traces of environmental information manipulation will be charged with higher interest spread if issuing banks adopt AI.

3 Methodology

3.1 Data

We select China as the focus to empirically explore our research question, for three reasons. First, green credit matters in China. Measuring the amount of green credit used by a firm has been difficult in previous research. As the largest emerging market and polluter, China has adopted comprehensive and strict policies to implement green credit. According to the Green Credit Guidelines 2012[3], every commercial bank (including national and regional banks) must evaluate loan applicants' environmental information and then adjust loan contracts. The contract conditions must be worse (e.g. higher interest rate) if corporate environmental performance is bad (Xing et al., 2021). Compared to developed markets where only specific banks proactively consider applicants' environmental performance (Chen et al. 2021; Hrazdil et al. 2023; Wellalage and Kumar 2021), China's loan financing must take full account of green credit, and is thus appropriate to our paper (Xing et al., 2021). Second, external financing matters for China's firms. Similar to other emerging markets, China's firms face severe financing constraints. They need abundant external funds to maintain development (Chan et al., 2012). As bank loans are the dominant method of financing in China, it is increasingly common for firms to use environmental information manipulation to try and satisfy

[3] The policy of Green Credit Guidelines is the first green credit policy of China, which was published by China's central bank and central government in 2012. Although China has other green finance practices such as green bonds, green insurance, green securities, etc., the influence of green credit is much greater.

banks' reviews. Plenty of studies suggest that banks should be alert to corporate strategic environmental behaviours (Du, 2015; Lyon and Montgomery, 2013; Xing et al., 2021; Zhang, 2022). This supports use of loan contracts to discuss issues around green credit. Third, AI matters for China's banks. Although there is a strong worldwide trend towards digitalization, some banks are still cautious because they worry over the stability of the financial system if they rely more on computing programs (Wang et al., 2024a). Nonetheless, digitalization and AI are more acceptable among China's banks. Tonghuashun, a famous Chinese financial statistics firm, reported in 2023 that almost all China's banks implemented digital systems to assist their business, and many of them employed AI in financing services. Such bank practices provide a wider research horizon and enrich the data for our paper.

We use China's loan contracts from 2019 to 2023 as the sample. The firms applying for these loans are listed firms whose financial data are public. Lending banks are the main business banks of China (Big 4 stated-owned banks, national banks, regional banks, etc.). We thus match three types of data to every loan contract, namely loan contract, firm and bank data. We select 2019 as the beginning year for the development of AI. Although AI has been developing for decades, it is only in recent years that it has been applied, reflecting earlier limitations of computing power. In our data collection process, we find no evidence of banks' AI adoption before 2019, and those years thus cannot expand our sample. Raw loan contract and financial data are collected from the CSMAR, CNRDS, and WIND databases, while AI data are manually collected and the data for corporate degrees of environmental information manipulation are collected via a machine learning approach described by Li (2010) and Xing et al. (2024). We omitted loans with missing data from our sample. All continuous variables are winsorized at 1% and 99% levels, to reduce the impact of outliers. The final sample contains 1209 loan contacts from 490 unique firms and 145 unique banks.

3.2 Variables and Models

3.2.1 Dependent Variable

Because we are studying loan financing, our dependent variable is loan contract condition. Consistent with Attig et al. (2021) and Chen et al. (2021), we use loan interest spread (*Spread_loan*) to measure it (in percentage). Similar to other developed markets, interest rate is the most important indicator. Banks charge an interest premium to hedge loan risks, i.e., loan interest spread, specified as the gap between the benchmark interest rate and the actual interest rate. The benchmark interest rate is set by the central bank of China and adjusted to implement monetary policy. Although other factors can also show as loan contract conditions, including loan amount and loan maturity, they are less reliable than interest spread in China because firms can quote different loan amounts and maturities according to their financing demands (Xing et al., 2021). Interest rate spread is objectively decided by banks. Previous literature finds that banks increase spreads for firms with poor environmental performance (Chen et al. 2021). This further supports our use of loan spread to discuss the role of AI.

3.2.2 Explanatory Variables

This paper uses two groups of explanatory variables. The first one is banks' AI adoption. Different from studies on corporate AI which is general and fuzzy (Chotia et al., 2024; Yu et al., 2024), we look at the adoption of AI in granting loans. For information on banks' use of AI in lending, we collect materials from three sources. First, we collected banks' annual reports, where they narrated what new technologies, of which AI is important, were developed and deployed in the past year. Second, we reviewed media coverage and historical official websites of all banks to find evidence of AI adoption. Most emerging technologies and their introductions will be publicized when a bank employs them. Finally, we consult staff of the banks in our sample to verify AI adoption levels. This process is accomplished by on-the-spot surveys, telephone visits and online consultation. Our raw data analysis then determined each bank's AI strategy and AI level referring to emerging literature on corporate AI adoption, measured by two variables: 1) AI strategy (*AIStrategy_bank*), a dummy variable which equals 1 if a bank deploys AI in the current year; and 2) AI level (*AILevel_bank*), a hierarchical variable whose values are 0 to 3, indicating no AI adoption to comprehensive AI adoption. Specifically, when a bank uses AI to assist staff in business (such as improving material review efficiency), but all review and decision processes are still accomplished by human staff, *AILevel_bank* equals 1. When AI can automatically review firms' materials and give advice but the final decision is still made by human staff, *AILevel_bank* equals 2. When AI can independently finish all review and decision processes, *AILevel_bank* equals 3. This means that banks and their AI systems have complete analysis and risk-control capabilities. In our surveys, most AI-implemented banks are graded at levels 1 or 2, with only some advanced banks achieving level 3.

The second explanatory variable is the degree of corporate environmental information manipulation, for which we use notation *EIM_firm*. This variable measures misleading claims of green credit in combination with the dependent variable, based on previous literature on corporate greenwashing and environmental information manipulation in disclosure (Walker and Wan 2012; Xing et al. 2024). We use a naïve Bayesian machine learning approach to calculate it, as described by Li (2010) and Xing et al. (2024). The detailed process of measurement is shown in Appendix A. In brief, we analysed all sample firms' environmental reports, and classified every sentence in the reports into three types by machine learning techniques: symbolic information, substantial information, and neutral information. According to the original definition of environmental information manipulation as the disparity between symbolic and substantial environmental information, *EIM_firm* equals the ratio of symbolic information minus the ratio of substantial information. We then standardized this variable. When *EIM_firm* equals 0, the firm has lowest environmental information manipulation degree, while a higher value of *EIM_firm* indicates severe environmental information manipulation.

3.2.3 Control Variables

As the loan contracts connect banks and firms, the control variables show characteristics of firm, loan, and bank. The selection of control variables is based on previous studies on banking, finance and loan research. First, in the firm characteristic group, we controlled: 1) firm size (*Size_firm*) which equals the natural logarithm of corporate total assets; 2) firm financial leverage (*Leverage_firm*) measured by the asset-liability ratio; 3) financial performance (*ROA_firm*) which equals the return on assets; 4) asset tangibility (*PPE_firm*) which equals the proportion of fixed assets to total assets; 5) financing constraints (*KZ_firm*) measuring by the KZ index[4]; 6) cash holding (*Cash_firm*) which equals the proportion of cash to total assets; and 7) corporate ownership (*SOE_firm*) which equals 1 if the firm is stated-owned.

Second, the characteristics of loan contract include: 1) syndicated loan

[4] KZ index is developed by Kaplan and Zingales (1997), whose calculation is based on several financial indicators such as market performance, dividend policy, financial conditions. A higher index indicates that the firm faces severe financing constraints. This index has been extensively adopted in prior research on corporate finance (Liu et al. 2022; Wu and Shen 2013).

(*Syndicate_loan*) which equals 1 if the loan is syndicated[5]; 2) loan maturity (*Maturity_firm*) which equals the number of years to the maturity of the contract; 3) loan amount (*Amount_loan*) which equals the natural logarithm of the loan amount (in CNY); 4) benchmark interest rate (*BaseRate_loan*) which equals the benchmark interest rate formulated by China's central bank when the loan was granted; 5) mortgages (*Mortgage_loan*) which equals 1 if the loan contract has mortgages.

Third, we controlled for bank characteristics, including: 1) bank size (*Size_bank*) measured by the natural logarithm of total assets of a bank; 2) bank's credit rating (*Credit_bank*) which is a graded variable ranging from 1 to 5[6]; 3) Interest-bearing assets (*IntAsset_bank*) measuring by the proportion of interest-bearing assets to total assets of a bank; 4) bank performance (*ROA_bank*) which equals a bank's return on assets; 5) the big four banks (*Big4_bank*) which equals 1 if a bank is one of the largest four banks of China; and 6) bank-firm regional nexus (*SameREG*) which equals 1 if the bank and applicant firm are in a same region.

We also controlled a series of fixed effects dummy variables. The first is the time fixed effect (*TIME*). We use the granularity of month because macroeconomics (such as monetary policies and GDP) may change monthly. The second is firm industry fixed effect (*IND_firm*). The third is firm region fixed effect (*REG_firm*). The fourth is bank region fixed effect (*REG_bank*). The final is loan aim fixed effect (*Aim_loan*), which records seven loan purposes including working capital, material procurement, repayment of debt, branching, acquisition, project construction, and business operations. The specifications of the above variables are listed in Appendix B.

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5 When a loan contract is syndicated, the AI adoption and bank characteristics are based on the largest bank of the syndicated group. This is because most decisions on syndicated loans are made by the largest bank.

6 Such rating theoretically contains nine levels (from AAA to C), but the ratings of our sample banks are better than BB. Thus, we assigned 1 to 5 for measuring BB to AAA ratings.

3.2.4 Models

The regression models are shown in Eq.1 and Eq.2, in which i indicates firms, j indicates banks, and t indicates times. α is the constant, *Controls* represents control variables, and ε indicates the random error term. Eq.1 is a priori to verify the phenomenon of preferential loans driven by environmental information manipulation. We expect that the coefficient of *EIM_firm* (β_1) is negative, meaning that firms with a higher degree of environmental information manipulation can obtain preferential loan contracts. This is contrary to the original design of green credit. In Eq.2, we added the interaction of AI, i.e., *AIStrategy_bank*×*EIM_firm* and *AILevel_bank*×*EIM_firm*. They are the focus of our research and can test the hypothesis. We expect their coefficients (β_0) to be significantly positive, suggesting that bank's AI can mitigate the effect of environmental information manipulation on loan contract conditions. In further analysis, we employ additional methods to test robustness such as instrumental variables, entropy matching, alternative models, etc.

$$Spread\_loan_{i,j,t} = \alpha + \beta_1 \times EDD\_firm_{i,j,t} + \sum Controls_{i,j,t} + \varepsilon \qquad \text{Eq.1}$$

$$\begin{aligned} Spread\_loan_{i,j,t} & \qquad \text{Eq.2} \\ &= \alpha + \beta_0 \times EDD\_firm_{i,j,t} \times AIStrategy\_bank(AILevel\_bank)_{i,j,t} \\ &+ \beta_1 \times EDD\_firm_{i,j,t} + \beta_2 \times AIStrategy\_bank(AILevel\_bank)_{i,j,t} \\ &+ \sum Controls_{i,j,t} + \varepsilon \end{aligned}$$

3.3 Summary Statistics

Summary statistics for the above variables are shown in Table 1. Panel A illustrates the basic information. We find that banks usually charge a premium for loan financing as the mean value of *Spread_loan* is 2.238. This is because China's firms usually suffer higher financing constraints and the resources of financing are limited. This is also indicated by the mean value of *KZ_firm* which is 2.394. AI is widely used among China's banks since the mean value of *AIStrategy_bank* is 0.499 and that of *AILevel_bank* is 0.877. About 19.8% loan contracts of our sample is mortgages and of 15.9% contracts are granted by the big four banks.

Panel B analyses the mean value differences of loan and bank characteristics between banks with and without AI adoption. We find that when a bank implements AI, it prefers to grant preferential loan contracts as the spread is lower, maturity is longer, and the amount is slightly larger. However, according to the comparisons of *Size_bank*, *Credit_bank*, *ROA_bank*, and *Big4_bank*, AI is more popular among advanced banks such as large-sized banks, high-rating banks, well-performed banks, and big four banks. We also find that banks are less likely to use AI in cross regional business because the mean value of *SameREG* is lower when a bank employs AI.

Finally, in Panel C, we focus on the firm and loan characteristics and analyse the mean value differences between firms with higher or lower degrees of environmental information manipulation. We classified the firms whose values of *EIM_firm* are larger than the median in the current year into the higher group[7]. We find that higher degrees of environmental information manipulation are more prevalent in SOEs and firms with larger size and better financial condition. This may be because such firms have more political connections. From an institutional perspective, politically-connected firms are more willing to engage in rent-seeking, such as using symbolic environmental behaviours to please regulators (Chen et al., 2011). Furthermore, environmental information manipulation degrees can be found for large

[7] The median values are calculated based on the sample of whole firms which is the same as the sample in Appendix A, rather than the loan contract sample.

amount loans, mortgage loans, and non-syndicated loans.

[Insert Table 1 about here]

4 Results

4.1 Baseline Results

4.1.1 Validation of the Relationship between Environmental Information Manipulation and Preferential Loan Contracts

We first test the existence of preferential loans driven by environmental information manipulation using regression Eq.1 which is a prerequisite for the hypothesis test. As only higher degrees of environmental information manipulation lead to preferential loan contracts, we can further analyse the mitigating role of banks' AI. The results are shown in Table 2, where column (1) displays the pooled regression result and column (2) shows a more unbiased result with fixed effects. Both results confirm that corporate environmental information manipulation can help firms acquire lower loan spread as the coefficients of *EIM_firm* are significantly negative at 1% levels (β = -4.111, $p < 0.01$ in column (1); β = -6.614, $p < 0.01$ in column (2)). We use the result of the fixed effects regression and calculate that the coefficient of *EIM_firm*'s economic significance is 0.216[8], implying that when firms improve degrees of environmental information manipulation by one standard error, their loan interest rates will reduce about 0.22% (deflated by the benchmark rate).

Several control variables are significant. For instance, the coefficients of

[8] Based on Mitton (2024), the calculation of economic significance is $\left|\frac{\beta \cdot \delta_x}{\bar{y}}\right|$, where β is the regression coefficient, δ_x is the standard of independent variable, and $\bar{y}$ is the mean value of dependent variable.

Size_firm, *PPE_firm*, *Cash_firm*, and *SOE_firm* are significantly negative, indicating that larger firms, stated-owned firms, and firms with more tangible assets and cash assets are more likely to obtain preferential loan contracts. However, financing constrained firms face more expensive loans as the coefficient of *KZ_firm* is positive. Syndicated and mortgage loans have higher spread as the coefficients of *Syndicate_loan* and *Mortgage_loan* are positive. This can be attributed to the amounts of such loans usually being larger with higher risks. The coefficient of *Maturity_loan* is negative. This may be because of the characteristics of long-term borrowers in China. Such firms are usually larger firms with more stable performance, and hence banks are willing to provide cheaper loans for long-term profits. Finally, we find that the coefficients of *Size_bank*, *Credit_bank*, and *IntAsset_bank* are significantly positive, implying that larger and high-rated banks are more cautious. Nevertheless, the coefficient of *Big4_bank* is negative and opposite to *Size_bank*. This may be because the big 4 are stricter in selecting clients which are usually well-performed to maintain lower loan costs (such as larger firms).

[Insert Table 2 about here]

4.1.2 Hypothesis Test: The Effect of AI

Based on the results in Table 2, we added the interaction of AI variables to test the hypothesis whose results are presented in Table 3. We show the effect of banks' adoption of AI (*AIStrategy_bank*) in column (1), and banks' AI levels (*AILevel_bank*) in column (2). We classified the sample into AI group (*AIStrategy_bank* = 1) and no-AI group (*AIStrategy_bank* = 0) with the comparison listed in columns (3) and (4). This classification can supplement the findings. In line with our expectation, banks' AI adoption can significantly reduce the effect of environmental information manipulation. According to the first two columns, the coefficients of both *AIStrategy_bank×EIM_firm* (β = 4.110, $p < 0.01$) and *AILevel_bank×EIM_firm* (β = 2.739, $p < 0.01$) are positive at the 1% levels. Correspondingly, the coefficient of *EIM_firm* is insignificant in column (3) for banks that have adopted AI (β = -2.129, $p > 0.1$), whereas it is significant in column (4) and similar to the results of Table 2 (β = -10.052, $p < 0.01$). These suggest that banks' AI is effective to mitigate the impact of corporate environmental information manipulation on preferential loan contracts. Therefore, our findings are supportive of the hypothesis (H1).

[Insert Table 3 about here]

4.2 Cross-sectional Analyses

The above discussion shows the heterogeneities of AI. Moreover, the effects of AI may change for different borrowers and creditors. Cross-sectional analyses on firms and banks are necessary because they can explain the boundaries of AI implementation. As our topic is green credit, we focus on the green attributes of firms and banks. Firstly, we compare a typical classification of polluting and non-polluting industries. Firms in these two industries have distinct environmental performance, strategies, and behaviours. Secondly, we find that some banks in China accumulate abundant experience of green credit while others do not. These can also change the effect of AI.

4.2.1 Polluting Firms vs. Non-polluting Firms

According to the classification published by the Ministry of Environmental Protection of China in 2010, 16 industries are defined as polluting, including thermal power, steel, cement, electrolytic aluminium, coal, etc. We allocated the samples of the firms belonging to these industries to the polluting firm group, and other firms to the non-polluting firm group. Compared to non-polluting firms, the polluting firms are more obvious for bank environmental review. Their environmental information manipulation may be detected even if banks do not implement any AI. This is an embodiment of signalling theory. The polluting image signals that the firms have stronger motivation to employ environmental information manipulation to disguise their conduct and acquire more financing resources (Seele and Gatti, 2017). Hence, banks may have carefully checked them to avoid being misled by such signals. We expect that the effect of AI is more prominent in the non-polluting firms.

The results of the comparison between polluting and non-polluting firms are shown in Table 4. Columns (1) and (3) listed the results of polluting firm sample, and columns (2) and (4) are those of non-polluting firms. We find that the coefficients of interactions become insignificant in the polluting firm group (β = 0.779, $p > 0.1$ in column (1); β = -0.233, $p > 0.1$ in column (3)), but those in the non-polluting group are still significantly positive (β = 5.522, $p < 0.01$ in column (2); β = 3.440, $p < 0.01$ in column (4)). Furthermore, we compare the differences between the coefficients, and the tests show they are significant, in line with our expectations. Meanwhile, the coefficients of *EIM_firm* in polluting firm group are meaningful even though they are insignificant. They imply that polluting firms cannot obtain preferential loan contracts by environmental information manipulation, showing that firms' polluting image will trigger banks' caution in granting loans.

[Insert Table 4 about here]

4.2.2 Green-experienced Banks vs. Inexperienced Banks

We define "green experience" as the knowledge and skills regarding environmental protection and sustainable development, in which those of green credit are crucial for banks. Although green credit has been implemented in China for over a decade, green experience between banks is different. Banks with abundant green experience are more sensitive to applicants' environmental information (Seele and Gatti, 2017). In this case, AI plays the role of catalyst. When a green-experienced bank suspects a firm's environmental disclosure, AI can more effectively determine whether the disclosure is manipulated. This can create a positive regeneration that the AI will be more intelligent after rounds of iteration. However, inexperienced banks may ignore some key clues of environmental information manipulation, and their AI instruments will be inefficient in design and operation. Therefore, we divide our sample into two groups - green-experienced and inexperienced banks. As the green attribute of loan business is common in the context of China's green credit, we shed light on the emerging field of green bonds, which is not a traditional business for the banking sector. Nevertheless, some Chinese banks issued green bonds to acquire market share. Banks issuing green bonds should be more green-experienced because such businesses need more environmental skills and knowledge in China (Lin and Su, 2022). We classified the loan contracts from banks which issued green bonds into the green-experienced group, with the others which did not issue green bonds into the inexperienced group. We expect that AI is more effective in the green-experienced group.

The results for the different banks are shown in Table 5. Columns (1) and (3) show the results of green-experienced group, and columns (2) and (4) are those of the inexperienced group. All coefficients of interactions are significantly positive (β = 19.617, $p < 0.01$ in column (1); β = 4.986, $p < 0.01$ in column (2); β = 7.203, $p < 0.01$

in column (3); $\beta = 3.501$, $p < 0.01$ in column (4)). Nevertheless, the comparison tests confirm that the coefficient in column (1) is significantly greater than that in column (2), and the coefficient in column (3) is significantly greater than that in column (4). These are in line with our expectation, suggesting that AI can address the issue of green credit especially in banks with more green experience.

[Insert Table 5 about here]

4.3 Channel Analyses

In hypothesis development, we narrated two channels of AI, namely, risk identification capability and legitimacy. The former means that banks with AI can better detect manipulated corporate environmental information, and hence the risks related to loan solvency decrease. The latter suggests that AI can match the corporate information and policy requirements and reduce banks' legitimacy risks. We further explore these two channels, not only to support this research's rationale, but also to reveal the black box of green credit achieved by AI.

4.3.1 Channel of Risk Identification

We use the non-performing loan (NPL) ratio as a proxy to measure banks' risk identification capability. A lower NPL ratio implies that banks are more successful in controlling risks, including financial risk and environmental risk. As we suggested that environmental and financial risks of banks are concordant in China's green credit development, we expect that AI can reduce NPL ratio, and the relationship between environmental information manipulation and loan spread is mitigated by the lower NPL ratio. We establish the following simultaneous equations to test the above channel according to Di Giuli and Laux (2022). Firstly, AI variables (*AIStrategy_bank* and *AILevel_bank*) was regressed to channel variables (Eq.3). Secondly, we use the fitted value of the channel variables to substitute for original AI variables (Eq.4). This method is similar to instrument variable (IV) and can reduce the impact of endogeneity (Di Giuli and Laux, 2022). For the channel of risk identification, the channel variable is *rNPL_bank*, which is the negative of a bank's NPL ratio (zero minus NPL ratio). Thus, a greater *rNPL_bank* value indicates less non-performing loan and lower risks. The fitted value variables are *rNPLS_bank* and *rNPLL_bank*, corresponding to *AIStrategy_bank* and *AILevel_bank*, respectively.

$$\begin{aligned} ChannelVariables_{i,j,t} &= \alpha + \beta_1 \times AIStrategy\_bank(AILevel\_bank)_{i,j,t} + \sum Controls_{i,j,t} \\ &+ \varepsilon \end{aligned} \qquad \text{Eq.3}$$

$$\begin{aligned} Spread\_loan_{i,j,t} &= \alpha + \beta_0 \times EDD\_firm_{i,j,t} \times Channel\widehat{Variables}_{i,j,t} \\ &+ \beta_1 \times EDD\_firm_{i,j,t} + \beta_2 \times Channel\widehat{Variables}_{i,j,t} \\ &+ \sum Controls_{i,j,t} + \varepsilon \end{aligned} \qquad \text{Eq.4}$$

The results of the channel of risk identification are presented in Table 6, where columns (1) to (2) are the first stage results and columns (3) to (4) are from the second stage. The results show that banks' AI will facilitate banks' risk control because the coefficients of *AIStrategy_bank* and *AILevel_bank* are significantly positive ($\beta = 0.096$, $p < 0.01$ in column (1); $\beta = 0.047$, $p < 0.01$ in column (2)). In columns (3) and (4), the interactions between the fitted value variables and corporate environmental information manipulation (*rNPLS_bank×EIM_firm* and *rNPLL_bank×EIM_firm*) are also significantly positive (β = 10.582, $p < 0.05$ in column (3); β = 12.041, $p < 0.05$ in column (4)). Such results support banks' AI adoption mitigating the problem of green credit by the channel of risk identification.

[Insert Table 6 about here]

4.3.2 Channel of Legitimacy

We collect environmental penalty data to measure banks' legitimacy. AI should be beneficial for banks' analysis efficiency on institutions and policies. In the field of green credit, AI can further improve the degree of legitimacy by excluding human interference, and help banks make further correct decisions in line with the institutions and legitimacy on reviewing corporate environmental information manipulation. Finally, the green credit issue will be addressed by AI due to banks' motivations of legitimacy conformity. We use the number of banks receiving environmental penalties in a year to measure the channel. We also utilize Eqs.3 and 4 as the methods and the negative value as the variable, namely, *rPenalty_bank*. with a greater number representing a greater degree of legitimacy capability. The notions of fitted values are *rPenaltyS_bank* and *rPenaltyL_bank*, corresponding to *AIStrategy_bank* and *AILevel_bank*, respectively.

The results of the legitimacy capability channel are shown in Table 7. Columns (1) to (2) are the first stage while columns (3) to (4) are the second stage. They suggest that AI can improve banks' environmental legitimacy because the coefficients of *AIStrategy_bank* and *AILevel_bank* are significantly positive (β = 0.343, $p < 0.01$ in column (1); β = 0.223, $p < 0.01$ in column (2)). The interactions are also in line with our expectation as *rPenaltyS_bank*×*EIM_firm* and *rPenaltyL_bank*×*EIM_firm* are also significantly positive ($\beta = 3.861$, $p < 0.01$ in column (3); $\beta = 4.893$, $p < 0.01$ in column (4)). Such results confirm the channel of legitimacy.

[Insert Table 7 about here]

4.4 Endogeneity Tests and Robustness Checks

4.4.1 Considering Reverse Causality

In the baseline analysis, we show that corporate environmental information manipulation can reduce loan spread, and banks' AI can mitigate this relationship. We attribute such effects to AI's capability. Nevertheless, these findings may face the endogeneity problems of reverse causality. For example, firms which acquired low-interest loans are more likely to exploit environmental information manipulation to disguise manipulated information, or banks may employ AI systems after they granted preferential loans to monitor the usage of the funds. Thus, determining causality is necessary for our research. We select instrumental variables (IVs) to address this endogeneity problem. Following Che et al. (2023) and Xing et al. (2024) who focus on corporate environmental disclosure or digitalization, we use spatial macro levels of the relevant independent variables as the IVs (i.e., *EIM_region*, *AIStrategy_region*, *AILevel_region*). Specifically, we calculate the average degrees of corporate environmental information manipulation and banks' AI adoption in every province. Theoretically, regional degrees are highly associated with individual degrees because both corporate environmental behaviours and banks' strategies have spill-over effects in the same region. Meanwhile, macro variables are usually exogenous to micro variables (Xing et al., 2024). These fulfil the correlation and exogeneity requirements of the IV method. In regressions, we firstly use every explanatory variable (*EIM_firm*, *AIStrategy_bank*, *AILevel_bank*) as the dependent variable and use corresponding IVs (macro variable) as independent variables to calculate fitted values (*hatEIM_firm*, *hatAIStrategy_bank*, *hatAILevel_bank*), and we then replace the explanatory variables in Eq.2 by the fitted values. The coefficients of the replaced interactions suggest net effects with minimal endogeneity.

The results of IVs are shown in Table 8, where columns (1) to (3) are the first-stage results and columns (4) to (7) are the second-stage and our focal results. In the first stage, IVs are effective as their coefficients are significantly positive. In the second stage, we find that the coefficients of the interactions are significantly positive in both 2SLS and GMM methods, suggesting that our main findings still hold. Thus, the reverse causality problem does not change our conclusions.

[Insert Table 8 about here]

4.4.2 Considering the Bias of Environmental Information Manipulation

We further consider the endogeneity problem of sample bias. The first type of bias is from corporate environmental information manipulation. Many firm characteristics are significantly different between firms with higher and lower degrees of environmental information manipulation. Our baseline results may result from such differences instead of environmental information manipulation. Following Rupar et al. (2024), we adopt entropy matching to address this problem. In the matching process, we classify firms into two groups with higher and lower degrees of environmental information manipulation[9], and select firm characteristics shown in the variable section as the covariates. The results are shown in Table 9. Panel A suggests that the differences

[9] The classification method is the same as that in section 3.3 and Table 1, Panel C.

in the covariates between two groups is minimal after matching. In Panel B, we find that the coefficients of the interactions are significantly positive, showing that the bias among firms does not impact the baseline results.

[Insert Table 9 about here]

4.4.3 Considering the Bias of AI Adoption

Another type of bias is attributed to differences between banks. Some characteristics can affect whether a bank implements AI systems or not. In this case, our original findings may be misleading because the real driving factors are bank characteristics. We employ entropy matching to mitigate such problem. We classify our sample into AI-implemented group and non-implemented group, and use the characteristics shown in the variable section as the matching variables. Table 10 shows the results, which are in line with our expectation. In Panel A, the matching is efficient since less difference exists between groups after matching. The coefficients of interactions after matching are positively significant in Panel B. These indicate that the bias between banks cannot change our baseline findings.

[Insert Table 10 about here]

4.4.4 Sample of Survey Data

Our sample of baseline analysis is based on the listed firms' loan contract data. However, this sample has two flaws. First, firms in this dataset are usually medium to large sized. We cannot detect the role of AI in small firms. Second, compared with listed firms, small firms' loan application may be directly rejected by banks (as credit rationing), which our sample cannot detect. We employ data from a survey named "China Small and Medium Enterprise Survey (CSMES)" to alleviate such problems. This survey is supported by two major programs of China and was launched in 2015. Many articles using this data discuss topics regarding corporate finance, fintech, and firm development (Xiang et al., 2019; Zhang et al., 2023). In the most recent data from 2023, CSMES added a branch survey on the AI adoption of every firm's counterpart bank, which refers to the bank receiving the firm's loan application. The sample contains 121 small and medium enterprises (SMEs), Every SME is marched with its major bank, whose AI adoption degree is also measured by a three-point scale. The dependent variable of this survey data is *Loan*, which is a self-perception variable measured by a Likert seven-point scale. Firms' executives answer the question in accordance with their experience and intuition. A greater value indicates that a firm has a higher success rate in obtaining loans:

Q: How important is it that your firm acquires a bank loan? (1 to 7)

We referred to Du et al. (2018) to detect SMEs' degrees of environmental information manipulation by comparing two answers in the survey questionnaire. First is the general question listed at the beginning section on the questionnaire:

Q: Did your firm make considerable contributions to environmental protection in the last year? (1 = totally disagree to 5 = total agree)

Second is the verifying question listed at the end:

Q; How much had the firm invested in environmental protection in the last year? (1 = none, 2 = less than 0.1% of year sale, 3 = less than 1% of yearly sale, 4 = less than 5% of yearly sale, and 5 = more than 5% of yearly sale)

We use the difference between the values of these two questions as the measurement of environmental information manipulation (*EIM*). The control variables include those firm characteristics: *Age* (firm age), *SOE* (equals 1 if a SME is stated-owned), *Employee* (number of employees in a firm), *Size* (total asset size), *Leverage* (the asset liability ratio), *ROS* (return on sale), *PPE* (fixed asset ratio), *BankCon* (equals 1 if the firm have long-term cooperation with the bank), and *IND* (industry effects).

The results from using the alternative survey data are shown in Table 11. The coefficient of *EIM* is significantly positive ($\beta = 0.170$, $p < 0.05$ in column (1); $\beta = 0.187$, $p < 0.05$ in column (2)), suggesting that SMEs with higher environmental information manipulation degrees are more likely to acquire loans. Nevertheless, the interactions are both significantly negative ($\beta = -0.258$, $p < 0.01$ in column (1); $\beta = -0.529$, $p < 0.01$ in column (2)). These results are similar to those from the baseline models. Therefore, the above tests confirm that our findings are robust.

[Insert Table 11 about here]

5 Discussion and Conclusions

5.1 Concluding Remarks

In this paper, we discuss an phenomenon of green credit and the role of AI in mitigating it. Based on 1209 loan contracts from 2019 to 2023, we find that corporate environmental information manipulation can help firms acquire loans with lower interest spreads, whereas banks' AI adoption can mitigate this influence. Based on information asymmetry theory, we attribute these findings to manipulated information and the effect of AI. We find that in the context of green credit, banks' AI systems can better identify the manipulated information in standardized and automatic ways. These strengthen the risk identification capability and legitimacy of banks, and we demonstrated these two channels. We also explored the boundaries of AI's effect. Finally, AI is more prominent in non-polluting firms and green-experienced banks. This is because AI's capability is substituted by the firm polluting attribute, but facilitated by the bank green attribute. We conclude that although firms can use some manipulated means to obtain green credit resources to which they are not entitled, banks can deploy advanced technologies such as AI to control the problem.

5.2 Theoretical Contributions

This paper contributes to information asymmetry theory in two ways. Firstly, we expand the theory to the field of AI. Information economics has strengthened the understand of market operation. One crucial conclusion is that asymmetric information is the underlying factor hindering market efficiency (Myers and Majluf, 1984; Nayyar, 1993). Mainstream studies on information asymmetry shed light on the solutions that improve the efficiencies of information collection and management (Cuadrado-Ballesteros et al., 2017; Daley and Green, 2012; Ferguson and Lam, 2023). Recent literature showed that digital technologies are beneficial for informational works (Li et al. 2024). Based on this, it is important to explore the relationship between information asymmetry and AI, which is considered as an emerging technology. Our paper employs a specific context and demonstrates a positive answer to one of the most important questions, whether AI is effective at reducing information asymmetry. Although this is connected to the basic rationales of previous research on digitalization's informational effect (Yang et al., 2023), we expand this significantly because AI technology is more capable than other digital technologies of eliminating asymmetric information and market friction. Our research is a valuable attempt and provides first-hand evidence that AI is a potentially correct and rational direction for building information-perfect markets.

Second, we propose a view of green credit affected by environmental information manipulation that is another priority contribution to information asymmetry theory. Compared with conventional finance business which has built completed audit and verification systems to control information friction, the consequences of asymmetric information in environmental affairs are more complex since most environmental information are multidisciplined and easily manipulated. This leads to environmental information manipulation (Crilly et al., 2012). Although studies have explained environmental information manipulation by information asymmetry theory (Crilly et al., 2012; Du, 2015; Guo et al., 2017), it is only one example of asymmetric information, whereas its circulation mechanisms in the market and economy have not been fully explored. We firstly define the process triggered by asymmetric information in combination with the behaviours and motivations of firms and banks, such as risk identification and legitimacy. Then, we show that appropriate instruments (e.g., AI) can reduce the degree of information asymmetry. Meanwhile, our heterogeneity and cross-sectional analyses not only indicate the condition of our findings, but also illustrate the boundary of information asymmetry theory in our topic. Accordingly, we developed a complete framework that is a new implementation of information asymmetry theory in the areas regarding sustainable development.

5.3 Implications

Our research highlights three practical implications for policymakers, banks, and firms. Firstly, as we emphasize the effect of AI, government departments can drive a more efficient market from supply and demand perspectives. In the financing supply side, governments can carry out relative guidelines to encourage banks' adoptions of

AI systems. In the financing demand side, governments can implement AI-supported environmental institutions to control environmental information manipulation behaviours. For instance, intelligent environmental assurance is feasible to improve information quality.

Secondly, this paper helps banks exclude “AI concerns” and can motivate them to construct efficient AI systems, especially in the trend of green credit. According to media coverage, AI is unacceptable to some people and organizations because of an absence of responsibility. For instance, when finance risks are exposed, banks can easily identify the person liable if the business is human-processed, whereas they cannot blame AI systems even when major works use such technologies. Thus, our paper provides a conclusion that organizations (e.g., banks for our research) adopting AI achieved higher efficiency and accuracy in reviewing information, even if it is complicated environmental information. This supports the banking sector’s use of AI technology to improve the stability of finance.

Finally, this paper also signals to firms that environmental information manipulation and other manipulated information become redundant with the development of digital technologies. firms should disclose their environmental actions in a more substantial way, and apply common disclosure standards such as GRI. Besides, our findings imply that AI not only identify environmental information manipulation but also supports honest disclosure. Firms with concrete information will obtain fairer conditions from corporate stakeholders. The implication of our findings for firms is that they should be more responsible in acquiring and using financial resources.

5.4 Limitation and Future Research

Our paper has some limitations, which point to future research opportunities.

We discuss the unethical phenomenon of green credit and its solutions of AI. However, AI and other emerging technologies may incur other unethical outcomes for environmental protection. For instance, we cannot infer the consequences when a firm uses AI to narrate environmental information manipulation, even if its counterpart stakeholders also deploy AI to review such information. This is a valuable topic based on our findings. but we do not report on it because of the deviation from our focus and the data limitations. We suggest that future research can answer this question. Such analysis can further consolidate the relationship between green credit and technology development. Besides, we use statistical data only to test our hypothesis, and the findings are general. Future research can use multiple methods such as qualitative study to focus on specific phenomena regarding AI implementation, green credit, or environmental information manipulation.

Appendix A. Measurement of Environmental Information Manipulation

Previous literature mainly uses textual analysis to detect firm's environmental disclosure or greenwashing degree (Du, 2015; Walker and Wan, 2012; Xing et al., 2021; Zhang, 2022). The basic procedure includes two steps: 1) determine substantial and symbolic environmental information; and 2) calculate the disparity between such two types of information. However, conventional methods are usually human-processed. Such manually collected data face two problems. First, data replication is difficult because people are difficult to give same evaluation for the texts in two rounds. Second, human evaluation is based on a person's subjective perception that may cause bias (Xing et al., 2024). Recent studies use emerging techniques to address these problems, and machine learning is effective. Thus, we also adopt a machine learning approach to measure environmental information manipulation degree.

The method of machine learning contains three steps. First, we disassemble corporate environmental disclosure. Considering symbolic and substantial information can occur in any sentence, we split the environmental reports into single sentences. This scheme is also adopted by Li (2010) who analyse corporate non-financial reports. Second, we define the attribute of every single sentence. In this step, we wielded the naïve Bayesian algorithm developed by Xing et al. (2024). This algorithm is trained by over thirty thousand sentences and can classify a sentence in corporate environmental report to one of three types, i.e., symbolic information, substantial information, and neutral information. The symbolic information refers to the sentence with beautified attributes but without concrete evidence. A typical sentence is "… *Our company adheres to the green concept that green mountains and clear waters are as valuable as gold and silver. We adhere to the leadership of innovation and work together with you to build a sustainable development path for the earth and create a better future* …". On the contrary, substantial information is the sentence supported by data or cases. For instance, "… *This year, our company has invested a total of 132.5 million yuan in environmental protection, achieving the aim of reducing carbon dioxide emissions by 4.5 million tons in total* …". Neutral information is usually the sentence that cannot gives relevant information such as corporate basic information.

After we classified every sentence of our sample firms' environmental disclosure, we calculate the variable of environmental information manipulation. According to Walker and Wan (2012), environmental information manipulation degree equals the proportion of symbolic sentences minus the proportion of substantial sentences. Finally, we normalized the variable and defined its theoretical range is [0, 1], representing no environmental information manipulation to total environmental information manipulation.

The procedure of the measurement is shown in Figure A1.

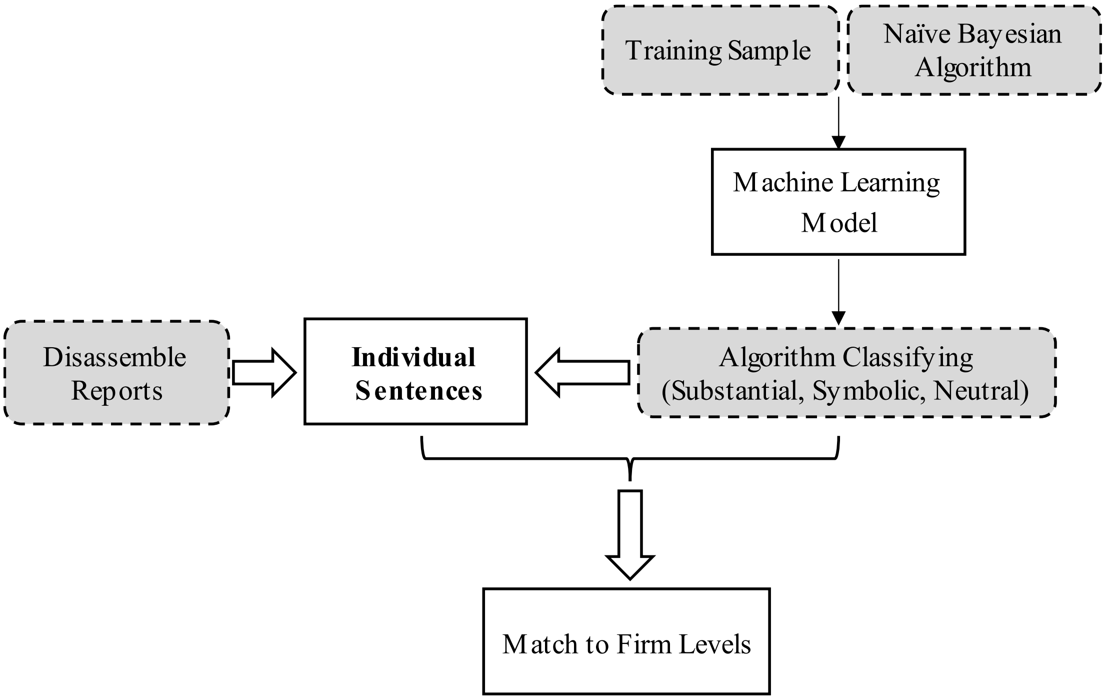

Figure A1. Measurement Procedure of Environmental Information Manipulation

Appendix B. Variable Specifications

The variable specifications are shown in following Table A1.

Table A1. Variable Specifications

Variable	Notation	Specification
Loan spread	*Spread_loan*	The gap between the benchmark interest rate and the actual interest rate.
Corporate environmental information manipulation	*EIM_firm*	Environmental Information Manipulation degree measured by a machine learning approach suggested in Appendix A.
Bank AI strategy	*AIStrategy_bank*	Dummy variable equals 1 if a bank deploys AI in the current year.
Bank AI level	*AILevel_bank*	Hierarchical variable whose values are 0 to 3 measures no AI adoption to comprehensive AI adoption.
Firm size	*Size_firm*	Natural logarithm of corporate total assets.
Firm financial leverage	*Leverage_firm*	Asset-liability ratio of firm.
Firm financial performance	*ROA_firm*	Return on assets of firm.
Firm asset tangibility	*PPE_firm*	Proportion of fixed assets to total assets.
Firm financing constraint	*KZ_firm*	Corporate KZ index.
Firm cash holding	*Cash_firm*	Proportion of cash to total assets.
Corporate ownership	*SOE_firm*	Dummy variable equals 1 if the firm is stated-owned.
Syndicated loan	*Syndicate_loan*	Dummy variable equals 1 if the loan is syndicated.
Loan maturity	*Maturity_loan*	Number of years to the maturity of the contract.
Loan amount	*Amount_loan*	Natural logarithm of the loan amount.
Benchmark interest rate	*BaseRate_loan*	Benchmark interest rate formulated by China’s central bank when the loan was granted.
Loan mortgages	*Mortgage_loan*	Dummy variable equals 1 if the loan contract has mortgages.
Bank size	*Size_bank*	Natural logarithm of total assets of a bank.
Bank credit rating	*Credit_bank*	Graded variable ranging from 1 to 5 measures bank credit rating.
Bank interest-bearing assets	*IntAsset_bank*	Proportion of interest-bearing assets to total assets of a bank.
Bank financial performance	*ROA_bank*	Bank’s return on assets.
Big4 banks	*Big4_bank*	Dummy variable equals 1 if a bank is one of the largest four banks of China.
Bank-firm regional nexus	*SameREG*	Dummy variable equals 1 if the bank and applicant firm are in a same region.
Time fixed effect	*Time*	A group of dummy variables measures monthly fixed effect.
Firm industry fixed effect	*IND_firm*	A group of dummy variables measures firm industry fixed effect.
Firm region fixed effect	*REG_firm*	A group of dummy variables measures firm region fixed effect.
Bank region fixed effect	*REG_bank*	A group of dummy variables measures bank region fixed effect.
Loan aim fixed effect	*Aim_loan*	A group of dummy variables measures loan aim fixed effect.

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Tables

Table 1. Summary Statistics

Panel A. Summary Statistics of All Variables

Variable	*N*	Mean	STD	Min	p25	p50	p75	Max
Spread_loan	1209	2.238	1.831	-1.650	1.300	1.750	3.000	9.000
EIM_firm	1209	0.327	0.073	0.044	0.272	0.347	0.376	0.521
AIStrategy_bank	1209	0.499	0.500	0.000	0.000	0.000	1.000	1.000
AILevel_bank	1209	0.877	1.038	0.000	0.000	0.000	2.000	3.000
Size_firm	1209	23.225	1.349	20.137	22.242	23.341	24.135	26.186
Leverage_firm	1209	0.587	0.189	0.147	0.475	0.577	0.693	0.997
ROA_firm	1209	0.007	0.079	-0.413	0.003	0.024	0.045	0.114
PPE_firm	1209	0.239	0.177	0.001	0.074	0.232	0.391	0.708
KZ_firm	1209	2.394	1.774	-1.114	1.029	2.379	3.664	6.728
Cash_firm	1209	0.146	0.088	0.008	0.077	0.134	0.208	0.392
SOE_firm	1209	0.626	0.484	0.000	0.000	1.000	1.000	1.000
Syndicate_loan	1209	0.130	0.336	0.000	0.000	0.000	0.000	1.000
Maturity_loan	1209	1.855	2.182	0.080	1.000	1.000	2.000	20.000
Amount_loan	1209	9.130	1.423	5.635	8.161	9.210	10.127	12.206
BaseRate_loan	1209	4.524	0.208	4.350	4.350	4.350	4.750	4.900
Mortgage_loan	1209	0.198	0.398	0.000	0.000	0.000	0.000	1.000
Size_bank	1209	26.036	1.141	24.349	25.264	25.775	26.638	29.434
Credit_bank	1209	3.299	0.528	1.000	3.000	3.000	4.000	5.000
IntAsset_bank	1209	0.692	0.088	0.473	0.643	0.709	0.750	0.906
ROA_bank	1209	0.089	0.013	0.065	0.078	0.089	0.098	0.129
Big4_bank	1209	0.160	0.366	0.000	0.000	0.000	0.000	1.000
SameREG	1209	0.519	0.500	0.000	0.000	1.000	1.000	1.000

Panel B. Mean Value Differences between Banks with and without AI Adoption

Variables	Banks without AI Adoption		Banks with AI Adoption		Mean Difference
	N	Mean	*N*	Mean	

Spread_loan	606	2.462	603	2.012	0.450***
EIM_firm	606	0.334	603	0.320	0.014***
Syndicate_loan	606	0.028	603	0.232	-0.204***
Maturity_loan	606	1.630	603	2.081	-0.451***
Amount_loan	606	9.095	603	9.164	-0.069
BaseRate_loan	606	4.498	603	4.549	-0.051***
Mortgage_loan	606	0.208	603	0.187	0.021
Size_bank	606	25.846	603	26.228	-0.382***
Credit_bank	606	3.201	603	3.396	-0.195***
IntAsset_bank	606	0.691	603	0.693	-0.003
ROA_bank	606	0.086	603	0.092	-0.006***
Big4_bank	606	0.012	603	0.308	-0.297***
SameREG	606	0.612	603	0.425	0.188***

Panel C. Mean Value Differences between Firms with Lower and Higher Degrees of Environmental Information Manipulation

Variables	Firms with Lower Environmental Information Manipulation		Firms with Higher Environmental Information Manipulation		Mean Difference
	N	Mean	*N*	Mean	
Spread_loan	858	2.259	351	2.186	0.072
Size_firm	858	23.051	351	23.65	-0.599***
Leverage_firm	858	0.589	351	0.585	0.004
ROA_firm	858	0.005	351	0.013	-0.008
PPE_firm	858	0.230	351	0.261	-0.032***
KZ_firm	858	2.588	351	1.921	0.666***
Cash_firm	858	0.145	351	0.151	-0.006
SOE_firm	858	0.585	351	0.726	-0.141***
Syndicate_loan	858	0.149	351	0.083	0.067***
Maturity_loan	858	1.807	351	1.972	-0.164
Amount_loan	858	9.046	351	9.335	-0.289***
BaseRate_loan	858	4.524	351	4.523	0.001
Mortgage_loan	858	0.185	351	0.228	-0.043*

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).

Table 2. Verification Results

	(1) Spread_loan	(2) Spread_loan
EIM_firm	-4.111***	-6.614***
	(-4.04)	(-4.44)
Size_firm	-0.072	-0.136**
	(-1.35)	(-2.13)
Leverage_firm	2.746***	0.706
	(5.44)	(1.29)
ROA_firm	0.264	0.902
	(0.33)	(1.04)
PPE_firm	-1.249***	-0.947**
	(-3.55)	(-2.08)
KZ_firm	-0.049	0.108*
	(-0.99)	(1.76)
Cash_firm	-2.816***	-2.746***
	(-4.09)	(-3.21)
SOE_firm	-0.504***	-0.482***
	(-4.16)	(-3.18)
Syndicate_loan	-0.018	1.572***
	(-0.09)	(4.46)
Maturity_loan	-0.091***	-0.064***
	(-3.95)	(-2.66)
Amount_loan	0.070*	0.010
	(1.75)	(0.27)
BaseRate_loan	0.346	0.327
	(1.10)	(1.11)
Mortgage_loan	0.845***	0.498***
	(6.39)	(3.41)
Size_bank	-0.020	0.588**
	(-0.40)	(2.57)
Credit_bank	-0.035	0.359**
	(-0.28)	(2.21)
IntAsset_bank	1.777***	1.805***
	(2.70)	(2.73)
ROA_bank	-8.931**	-7.933*
	(-2.23)	(-1.68)
Big4_bank	-0.809***	-0.653***
	(-7.87)	(-5.46)
SameREG	0.114	-0.160
	(1.04)	(-1.03)
Fixed Effects	No	Yes
Constant	2.867	-12.597*
	(1.29)	(-1.94)
N	1209	1209
Adj. R^2	0.305	0.542

Note: The first row represents the estimated coefficient, the number in parentheses represents the *t*-value of significance (corrected for heteroskedasticity). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).

Table 3. Results of AI's Effects

	(1) Full Sample *Spread_loan*	(2) Full Sample *Spread_loan*	(3) AI Sample *Spread_loan*	(4) No-AI Sample *Spread_loan*
EIM_firm×AIStrategy_bank	4.108***			
	(3.07)			
EIM_firm×AILevel_bank		2.739***		
		(4.49)		
EIM_firm	-6.046***	-5.827***	-2.129	-10.052***
	(-4.26)	(-4.20)	(-0.98)	(-4.78)
AIStrategy_bank	-0.448***			
	(-3.58)			
AILevel_bank		-0.239***		
		(-4.37)		
Size_firm	-0.138**	-0.151**	-0.156*	-0.221*
	(-2.19)	(-2.43)	(-1.91)	(-1.75)
Leverage_firm	0.828	0.838	0.646	0.356
	(1.53)	(1.55)	(0.75)	(0.40)
ROA_firm	0.848	0.732	0.827	1.145
	(1.04)	(0.90)	(0.56)	(0.74)
PPE_firm	-0.998**	-0.902**	0.267	-1.121
	(-2.21)	(-2.03)	(0.44)	(-1.07)
KZ_firm	0.086	0.088	0.060	0.225**
	(1.42)	(1.46)	(0.51)	(2.34)
Cash_firm	-2.981***	-2.969***	-0.425	-4.066***
	(-3.49)	(-3.53)	(-0.26)	(-2.91)
SOE_firm	-0.526***	-0.549***	-0.743***	-0.197
	(-3.46)	(-3.60)	(-3.39)	(-0.71)
Syndicate_loan	1.806***	1.754***	1.742***	1.794***
	(5.60)	(5.49)	(3.70)	(2.81)
Maturity_loan	-0.067***	-0.061***	-0.035	-0.037
	(-2.82)	(-2.63)	(-1.19)	(-0.76)
Amount_loan	0.015	0.012	0.034	0.104**
	(0.39)	(0.32)	(0.54)	(2.13)
BaseRate_loan	0.320	0.241	0.540	0.010
	(1.09)	(0.82)	(1.36)	(0.02)
Mortgage_loan	0.495***	0.478***	0.211	0.403*
	(3.53)	(3.46)	(0.87)	(1.88)
Size_bank	0.675***	0.652***	-0.080	1.180***
	(3.00)	(2.92)	(-0.17)	(3.59)
Credit_bank	0.375**	0.315**	0.111	0.513
	(2.36)	(2.04)	(0.57)	(1.43)
IntAsset_bank	1.574**	1.498**	1.551*	0.530
	(2.39)	(2.32)	(1.81)	(0.49)
ROA_bank	-2.617	1.521	-9.596*	38.316**
	(-0.57)	(0.33)	(-1.68)	(2.55)
Big4_bank	-0.415***	-0.379***	-0.385***	-1.390***
	(-3.06)	(-2.87)	(-2.72)	(-2.62)
SameREG	-0.168	-0.163	-0.173	-0.309
	(-1.10)	(-1.08)	(-0.77)	(-1.09)
Fixed Effects	Yes	Yes	Yes	Yes
Constant	-17.089***	-15.798**	5.447	-29.808***
	(-2.64)	(-2.46)	(0.41)	(-2.82)
N	1209	1209	603	606
Adj. R^2	0.554	0.560	0.525	0.728

Note: The first row represents the estimated coefficient, the number in parentheses represents the *t*-value of significance (corrected for heteroskedasticity). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).

Table 4. Cross-sectional Analyses on Polluting and Non-polluting Firms

	Polluting Firm	Non-polluting Firm	Polluting Firm	Non-polluting Firm
	(1)	(2)	(3)	(4)
	Spread_loan	*Spread_loan*	*Spread_loan*	*Spread_loan*
EIM_firm×AIStrategy_bank	0.779	5.522***		
	(0.36)	(2.99)		
EIM_firm×AILevel_bank			-0.233	3.440***
			(-0.33)	(4.08)
EIM_firm	-0.267	-6.971***	-0.480	-6.837***
	(-0.12)	(-3.88)	(-0.21)	(-3.94)
AIStrategy_bank	-0.079	-0.577***		
	(-0.40)	(-3.71)		
AILevel_bank			-0.077	-0.309***
			(-0.96)	(-4.65)
Control Variables	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Constant	-23.130**	11.946	-21.447**	11.817
	(-2.40)	(1.09)	(-2.35)	(1.11)
N	435	774	435	774
Adj. R^2	0.757	0.642	0.758	0.651
Chi^2 test for Difference	3.72*		14.63***	

Note: The first row represents the estimated coefficient, the number in parentheses represents the *t*-value of significance (corrected for heteroskedasticity). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).

Table 5. Cross-sectional Analyses on Banks with and without Green Experience

	Green Banks	Non-green Banks	Green Banks	Non-green Banks
	(1)	(2)	(3)	(4)
	Spread_loan	*Spread_loan*	*Spread_loan*	*Spread_loan*
EIM_firm×AIStrategy_bank	19.617***	4.986***		
	(3.52)	(2.90)		
EIM_firm×AILevel_bank			7.203***	3.501***
			(4.04)	(3.54)
EIM_firm	-17.492***	-4.530**	-15.478***	-3.887**
	(-5.04)	(-2.55)	(-5.12)	(-2.13)
AIStrategy_bank	0.625	-0.592***		
	(1.50)	(-3.49)		
AILevel_bank			0.270**	-0.306***
			(2.18)	(-3.84)
Control Variables	Yes	Yes	Yes	Yes
Fixed Effects				
Constant	3.639	-18.253**	-0.723	-16.924**
	(0.22)	(-2.29)	(-0.04)	(-2.14)
N	295	914	295	914
Adj. R^2	0.721	0.630	0.737	0.635
Chi^2 test for Difference	11.98***		5.74**	

Note: The first row represents the estimated coefficient, the number in parentheses represents the *t*-value of significance (corrected for heteroskedasticity). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).

Table 6. Results of the Risk Identification Channel

	(1) *rNPL_bank*	(2) *rNPL_bank*	(3) *Spread_loan*	(4) *Spread_loan*
AIStrategy_bank	0.096^{***}			
	(8.94)			
AILevel_bank		0.047^{***}		
		(10.30)		
rNPLS_bank×EIM_firm			10.582^{**}	
			(2.00)	
rNPLL_bank×EIM_firm				12.041^{**}
				(2.35)
EIM_firm			-6.344^{***}	-6.271^{***}
			(-4.16)	(-4.14)
rNPLS_bank			-4.959^{***}	
			(-3.76)	
rNPLL_bank				-5.415^{***}
				(-4.58)
Control Variables	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Constant	1.266^{**}	1.062^{*}	-13.369^{**}	-13.173^{**}
	(2.18)	(1.78)	(-2.07)	(-2.04)
N	1209	1209	1209	1209
Adj. R^2	0.667	0.672	0.551	0.555

Note: The first row represents the estimated coefficient, the number in parentheses represents the *t*-value of significance (corrected for heteroskedasticity). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).

Table 7. Results of the Legitimacy Channel

	(1)	(2)	(3)	(4)
	rPenalty _bank	*rPenalty _bank*	*Spread_loan*	*Spread_loan*
AIStrategy_bank	0.343***			
	(5.52)			
AILevel_bank		0.223***		
		(7.22)		
rPenaltyS_bank×EIM_firm			3.861***	
			(2.60)	
rPenaltyL_bank×EIM_firm				4.893***
				(3.36)
EIM_firm			-6.513***	-6.406***
			(-4.51)	(-4.53)
rPenaltyS_bank			-1.282***	
			(-3.47)	
rPenaltyL_bank				-1.066***
				(-4.30)
Control Variables	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Constant	-11.135***	-11.852***	-25.319***	-22.324***
	(-3.04)	(-3.23)	(-3.41)	(-3.27)
N	1209	1209	1209	1209
Adj. R^2	0.352	0.378	0.552	0.558

Note: The first row represents the estimated coefficient, the number in parentheses represents the *t*-value of significance (corrected for heteroskedasticity). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).

Table 8. Results of Instrumental Variables

	First-stage			Second-stage: 2SLS		Second-stage: GMM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	EIM_firm	*AIStrategy_bank*	*AILevel_bank*	*Spread_loan*	*Spread_loan*	*Spread_loan*	*Spread_loan*
EIM_region	0.754^{***}						
	(14.25)						
AIStrategy_region		0.874^{***}					
		(36.69)					
AILevel_region			0.911^{***}				
			(41.11)				
hatEIM_firm×hatAIStrategy_bank				3.273^{**}		50.866^{**}	
				(1.99)		(2.03)	
hatEIM_firm×hatAILevel_bank					2.519^{***}		17.769^{*}
					(3.01)		(1.92)
hatEIM_firm				-5.986^{**}	-4.805^{*}	2.000	-1.066
				(-2.00)	(-1.74)	(0.46)	(-0.37)
hatAIStrategy_bank				-0.856^{***}		-0.144	
				(-5.07)		(-0.55)	
hatAILevel_bank					-0.338^{***}		-0.165
					(-4.61)		(-1.56)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.337^{*}	0.147	2.107	-15.712^{**}	-14.339^{**}		
	(-1.71)	(0.12)	(0.83)	(-2.23)	(-2.04)		
N	1209	1209	1209	1209	1209	1209	1209
Adj. R^2	0.765	0.793	0.803	0.539	0.540		

Note: The first row represents the estimated coefficient, the number in parentheses represents the *t*-value of significance (corrected for heteroskedasticity). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).

Table 9. Entropy Matched Results of Firm Characteristics

Panel A. Mean Values before and after Match

Matching Variables	High Environmental Information Manipulation	Low Environmental Information Manipulation	
		After Match	Before Match
Size_firm	23.650	23.640	23.050
Leverage_firm	0.585	0.585	0.589
ROA_firm	0.013	0.013	0.005
PPE_firm	0.261	0.261	0.230
KZ_firm	1.921	1.921	2.588
Cash_firm	0.151	0.151	0.145
SOE_firm	0.727	0.726	0.585

Panel B. Regression Results.

	(1)	(2)
	Spread_loan	*Spread_loan*
EIM_firm×AIStrategy_bank	3.560^{**}	
	(2.20)	
EIM_firm×AILevel_bank		2.998^{***}
		(4.25)
EIM_firm	-5.162^{***}	-4.755^{***}
	(-3.72)	(-3.52)
AIStrategy_bank	-0.443^{***}	
	(-3.11)	
AILevel_bank		-0.192^{***}
		(-3.35)
Control Variables	Yes	Yes
Fixed Effects	Yes	Yes
Constant	-16.811^{***}	-16.405^{**}
	(-2.62)	(-2.56)
N	1209	1209
Adj. R^2	0.633	0.640

Note: The first row represents the estimated coefficient, the number in parentheses represents the *t*-value of significance (corrected for heteroskedasticity). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).

Table 10. Entropy Matched Results of Bank Characteristics

Panel A. Mean Values before and after Match

Matching Variables	Adopting AI	Non-adopting AI	
		After Match	Before Match
Size_bank	26.230	26.230	25.850
Credit_bank	3.396	3.396	3.201
IntAsset_bank	0.693	0.693	0.691
ROA_bank	0.092	0.092	0.086
Big4_bank	0.309	0.308	0.012
SameREG	0.425	0.425	0.612

Panel B. Regression Results.

	(1)	(2)
	Spread_loan	*Spread_loan*
EIM_firm×AIStrategy_bank	5.972^{***}	
	(4.38)	
EIM_firm×AILevel_bank		3.459^{***}
		(5.90)
EIM_firm	-7.234^{***}	-7.080^{***}
	(-4.43)	(-4.39)
AIStrategy_bank	-0.430^{***}	
	(-3.73)	
AILevel_bank		-0.240^{***}
		(-4.49)
Control Variables	Yes	Yes
Fixed Effects	Yes	Yes
Constant	-3.748	0.041
	(-0.47)	(0.01)
N	1209	1209
Adj. R^2	0.669	0.675

Note: The first row represents the estimated coefficient, the number in parentheses represents the *t*-value of significance (corrected for heteroskedasticity). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).

Table 11. Results of Survey Data

	(1)	(2)
	Loan	*Loan*
EIM×AIStrategy_bank	-0.529***	
	(-3.29)	
EIM×AILevel_bank		-0.258***
		(-3.41)
EIM	0.187**	0.170**
	(2.48)	(2.31)
AIStrategy_bank	0.774***	
	(3.11)	
AILevel_bank		0.408***
		(4.03)
Age	0.317*	0.321*
	(1.76)	(1.80)
SOE	0.680***	0.632**
	(2.83)	(2.40)
Employee	0.031	0.029
	(0.26)	(0.32)
Size	-0.191	-0.057
	(-0.94)	(-0.32)
Leverage	-0.274**	-0.235**
	(-2.37)	(-2.25)
ROS	-0.167	-0.189
	(-0.64)	(-0.77)
PPE	0.445*	0.418**
	(1.89)	(2.09)
BankConn	0.358*	0.217
	(1.66)	(1.10)
IIND	Yes	Yes
Constant	1.209	0.981
	(1.23)	(1.29)
N	121	121
Adj. R^2	0.353	0.426

Note: The first row represents the estimated coefficient, the number in parentheses represents the *t*-value of significance (corrected for heteroskedasticity). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two-tailed).