Artificial Intelligence Driven Responsible Green Finance

Abstract: We discuss the relationship between financial institutions' artificial intelligence (AI) and (ir)responsible green finance, where environmental-decoupled firms acquire external green finance resources. Using data on 1,209 loan contracts from 2019 to 2023 in China, which is one of the largest implementors of green finance, we find that banks employing AI are more likely to increase loan interest spread for firms with more decoupled environmental information, suggesting that AI is beneficial for responsible green finance. Large-model AI (compared with conventional AI), bilateral AI (compared with internal AI), and open-source AI (compared with closed-source AI) are more effective. The effect of AI is more prominent for loan contracts granted by green-experienced banks and those to non-polluting firms. We confirm the dual re-coupling channels that AI is beneficial for banks' risk identification and legitimacy capability. These findings contribute to the information asymmetry theory and literature on technological change, green finance, and corporate environmental behaviours.

Keywords: Artificial intelligence; Green finance; Environmental disclosure; Bank loan; Responsible finance

1 Introduction

Emerging technologies are rapidly changing global economic patterns. In recent decades, due to the development of big data, machine learning, neural network, etc., a growing number of enterprises, organizations, and individuals employ artificial intelligence (AI) and related instruments to promote operational efficiency (Aman et al., 2024; Bauer et al., 2023). In late 2022, OpenAI published its milestone product, ChatGPT, showing the great potential of AI, which has become one of the most influential large AI models. In mid-2024, the value of NVIDIA, a leader in hardware for AI computing, soared beyond 3.3 trillion USD, making it the most valuable firm in the world, surpassing Apple and Microsoft, reflecting the market preference for AI. As one of the most advanced information technologies, AI's application scenarios are various, in which finance is typical as it is information-sensitive and many standardized activities can be processed using AI (Rammer et al., 2022). For instance, the Industrial and Commercial Bank of China (ICBC), the largest bank in China, has established comprehensive AI-assistant programs covering document review and loan management (see Figure 1). However, in the field of green finance, the discussion on AI is scant. Compared to conventional finance based only on financial information (Doumpos et al., 2023; Rahman et al., 2023), green finance needs abundant environmental information for financing applicants (Homar and Cvelbar, 2021). Such information is more easily manipulated than conventional financial information, leading to the problem of (irresponsible) finance that is green in name only.

[Insert Figure 1 about here]

From a micro perspective, green finance refers to the inclusion of corporate environmental performance into financial institutions' criteria when firms seek external funds (Edmans and Kacperczyk, 2022; Stroebel and Wurgler, 2021)[1]. Responsible green finance is expected to combine environmental protection and finance, but finance that is green in name only distorts this principle (Ahlström and Monciardini, 2022; Hrazdil et al., 2023). It is criticised because enterprises can exploit superficially compliant environmental information for financing benefits, described as environmental decoupling in disclosure (Flammer 2021; Zhang 2022; Gull et al, 2023). Misleading branding of green finance is representative of "anti-environmentalism", aggravating the concern that green objectives and economic benefits are difficult to achieve simultaneously (Babiker et al., 2003; Marquis et al., 2016; Parguel et al., 2011). A discussion of whether AI can mitigate unreal representations around green finance is thus important for enterprises, financial institutions, and finance systems.

The major path to responsible green finance is solving decoupled environmental information (Marquis et al., 2016). Financial institutions thus have to break the information barriers to mitigate information asymmetry (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). The core difficulty is the trade-off between the cost and benefit of identifying information (Seele and Schultz, 2022). It is easy for financial institutions to pay too much for reviewing evidence on proving or disproving corporate environmental information (Schiemann and Sakhel, 2019). In this process, AI can generate standard automated procedures for reviewing information (Doumpos et al., 2023; Rahman et al., 2023). Efficient AI systems can reduce environmental information asymmetry, and be useful for correcting the decision-making process when environmental decoupling is prevalent. There is a relative dearth of prior literature on

[1] Green finance mainly focusses on financial activities of enterprises instead of those of governments or other state organizations. This is because enterprises are the dominant producers of industrial pollution.

the effect of AI on (ir)responsible green finance. Studies mainly discuss the separate financial effect of AI or corporate greenwashing behaviours (Doumpos et al. 2023; Xing et al. 2021; Zhang 2022), but such findings cannot provide a direct solution to environmental decoupling in disclosure. In the finance sector, even though some big banks such as ICBC suggest that they combine the patterns of green finance and digital finance, their performance is still in question and not universal. Reflecting this, the research question for this paper is whether a financial institution's adoption of AI can mitigate misleading claims about green finance, resulting from corporate environmental decoupling?

We select China as the focus to explore this question, for three reasons. First, green finance matters in China. Measuring the amount of green finance 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 finance, especially in the banking business. According to the Green Credit Guidelines 2012[2], 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 debt and loan financing must take full account of green finance, and is thus appropriate to our paper (Xing et al., 2021). Second, external financing matters for China's enterprises. Similar to other emerging markets, China's firms face severe financing constraints. They need abundant

[2] 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.

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 decoupling to try and satisfy 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 finance. 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.

Our sample contains 1209 loan contracts for listed firms in China from 2019 to 2023. We match firm- and bank-level variables to every loan contract. We especially focus on firms' environmental reports, which are the main source of environmental information, and thus analyse corporate environmental decoupling in information. We measured the degree of decoupling 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, official websites and mobile apps, and media coverage. We analyse the attributes of AI and its effect in combination noting the effect of information asymmetry and China's green finance background (Heimstädt, 2017; Lyon and Montgomery, 2013). Our baseline results confirm that banks' AI adoption can mitigate corporate use of decoupled information to obtain lower loan interest rates. We further discuss the heterogeneities of AI, including large-model AI vs. conventional AI, internal AI vs. bilateral AI, and open-source AI vs. closed-source AI. 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 are surprising and exciting because they confirm that AI is effective in exposing unrealistic claims about use of green finance, and are instructive for banks, regulators and enterprises.

This paper has three contributions to the literature. First, we contribute to the literature that discusses how technological change affects the development of green finance by exploring the effect of AI. Digitalization is rapidly adopted by many enterprises. 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 financial institutions 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, especially in China's banks, 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 by connecting it with (ir)responsible green finance. From an economic perspective, our findings provide original evidence on the nexus between technological change, financial stability, and sustainable development.

Second, we relate (ir)responsible green finance to the theory of information asymmetry. Green finance 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 finance may not achieve green objectives, reflecting decoupling (Zhang 2022). This problem is found in both developing and developed markets (Stroebel and Wurgler, 2021). Misleading information about green finance can have disruptive effects on confidence in green finance. Our paper, based on the Chinese situation, proposes a framework for dealing with misinformation on green finance and addresses this using emerging technologies such as AI. Therefore, as we discuss a solution to the use of misleading information for green finance, our findings are insightful for regulatory policies and financial institutions' strategies, helping to restoring confidence in green finance.

Finally, we also contribute to the literature on technological governance relating to irresponsible green behaviours and environmental decoupling. Many studies discuss the specification, proxy, and consequences of environmental decoupling, 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 decoupling is harmful to positive environmental development and should be resisted by firms' stakeholders. However, some literature finds that decoupled information 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 decoupling (Xing et al. 2021; Zhang 2022), we propose that AI can play a crucial role. Our main findings show that AI achieves re-coupling and mitigates misleading information on green finance, reflecting AI's capabilities at detecting and correcting environmental decoupling. Our heterogeneity and channel tests provide additional evidence. Such comprehensive discussions are beneficial for healthy environmental development.

2 Background, Literature, and Hypothesis

2.1 Institutional Background of China's Green Finance

China's green finance practices are greatly motivated by policies. In 2000s when green finance was still in the early stages in China, only specific regional governments proposed that local financial institutions should combine finance and environmental development (Lin and Ho 2011; Zhang 2022). However, in 2007, China's central government and central bank proposed that China implement green credit. In 2012, the guidelines of green credit policy were officially published, to comprise the first green finance policy in China. Along with the green credit policy, many related policies were specified, on environmental disclosure, regional environmental regulation, environmental rewards, etc. Meanwhile, other green finance products and related policies were developed. For instance, policies supportive of green bonds, green insurance, and green securities were implemented between 2020 to 2022. In early 2024, the central bank and five central government departments of China published comprehensive guidelines for green finance, covering environmental standards and disclosure, and international cooperation. Under these guidelines, China aims to build systemic green finance before 2035. In summary, green finance polices develop late but rapidly in China.

Green finance significantly changes the behaviours of China's financial institutions and enterprises. First, most financial institutions are required to review clients' environmental performance. For example, under the green credit policy, banks should provide stricter contract conditions (such as spread premium and credit rationing) if the applicants are rated low in environmental evaluation, i.e., "environmental veto" (Xing et al. 2021). Second and more importantly, firms enhance environmental activities to acquire more financial resources. Enterprises disclosing their environmental engagement become a typical method to cater to green finance policies. As a consequence, China's green finance policies play effective roles in specific cases. Many firms successfully acquired bank loans, issued green bonds, or participated in green insurance. Moreover, many new ventures in environmental protection industries have been established. According to the report of National Energy Administration of China, the investment amount in new energy and environmental industries grew beyond 2.8 trillion CNY (approximate 4,000 billion USD) in 2023, maintaining a high rate of increase.

According to the above discussion, green credit is dominant among the green finance policies and practices in China. This is not only because green credit has the longest development history in China, but also China's enterprises are more reliant on loan financing to acquire external funds. Similar to other emerging markets, firms in China suffer financing constraints and need financing to develop. As thresholds for initial public offering and bond issuance are relatively high, commercial banks in China control most financing for most companies. This Chinese characteristic encourages green credit development in China, and motivates firms to conform to the requirements of green credit policy. Many studies explore the impacts and economic consequences of green finance from China's green credit policy (Chen et al. 2021; Liu et al. 2024b; Xing et al. 2024; Zhang 2022). The crucial role of China's green credit can also be found in many government reports. For instance, the central bank of China reported in 2023 that green credit policies have become pillars of green upgrading of infrastructure, clean energy, and the energy conservation and environmental protection sectors. The use of green credit is significantly higher than other green finance activities such as green bonds or green insurance.

There are two main differences between China's and western countries' green finance. On one hand, China's green finance is policy-led and comprehensive. As discussed, the flourishing green finance practices of China (represented by green credit) reflects government guidelines and regulations that are classified as formal institutions. In some developed markets such as UK, many green finance practices are proactive. Literature finds that banks in such countries will punish loan applicants with worse environmental performance by increasing interest spreads (Attig et al., 2021; Hrazdil et al., 2023). This is because banks treat such applicants as higher risk. Bad environmental performance may reduce stakeholders' support and financial performance, and banks may face the problem of low solvency if they grant loans to such firms. We do not exclude the market motivation of China's banks, but China's green credit policy provides a systematic framework that all banks should comply with.

Another difference between Chinese and other countries' green finance is the typical finance pattern. We show that green credit is most important in China, whereas green securities or green bonds are more important in some developed markets. For example, the amount of green bond issues in the US were over 3,300 billion USD between 2015 and 2022, and green bonds have become the largest segment of green finance in US, far ahead of green credit and green insurance. One possible reason for this is the more mature financial market. Compared with China, investors and institutions in US financial markets are more professional and efficient. Banks mainly play a role of intermediary rather than investors (Berger et al., 2009). Nevertheless, although dominant finance patterns are different between China and other markets, the core of green finance is similar. Specifically, fund providers have to review the environmental information of applicants, and then make investment decisions. Reflecting these two differences, we suggest that bank loans are most appropriate to discuss green finance in China as they are green and influential. In this paper, we thus focus on bank loan contracts.

2.2 Literature on (Ir)responsible Green Finance and AI

The development of green finance policies and practices has stimulated research on its economic and environmental consequences. For instance, Edmans and Kacperczyk (2021) conclude that green finance has significantly changed the attitudes of enterprises and their stakeholders. In studies on green finance, Flammer (2021) finds that green bonds are more popular than conventional bonds in the US and help to cultivate corporate environmental performance. Similarly, in China where green credit is more common, 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 finance plays a positive role in enterprises and financial markets.

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

More importantly, greenwashing behaviours can affect the implementation of green finance, resulting in finance that is green in name only (or irresponsible green finance). Theoretically, the principal responsibility of green finance is allocating financing resources to truly green fields (Edmans and Kacperczyk, 2022). Thus, irresponsible green finance can be defined as the phenomenon that resources are misallocated to enterprises with symbolic or decoupled environmental behaviours or information (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 decoupled environmental information 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 decoupling of disclosure have more investment activities in green finance, because the information helps them receive more financing resources, and firms use such investment to disguise the decoupling. Attig et al. (2021) directly test the positive relationship between greenwashing and loan financing. Cao et al. (2022) and Liu et al. (2024a) use data on China's green finance and confirm that firms with greenwashed environmental disclosure obtain better loan contract conditions. These findings support the phenomenon of finance that is green in name but not in reality.

Another group of studies explores the governance of environmental decoupling and responsible green finance. First, appropriate external supervision and regulation can prevent firms from adopting decoupled environmental strategies. Liu et al. (2024b) suggest that collaborative regulation, through formal institutions, can control corporate greenwashing behaviours. Du (2015) finds that media, as an informal supervision mechanism, also play a governance role in corporate environmental decoupling. The crucial rationale of such governance is the information mechanism. Only when the decoupled environmental information 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 help construct responsible green finance. Xing et al. (2021) indicate that banks may be confused by decoupled environmental disclosure. We can thus infer that more concrete information supporting substantial positive corporate environmental performance helps banks make rational decisions. Nevertheless, investigating environmental decoupling is still challenging because banks cannot directly control corporate disclosure and the instrument for measuring environmental decoupling 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 for responsible green finance. This 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.

Although some emerging literature focuses on the "green" function of AI, the exploration of responsible green finance is limited. Limited research has shed light on the adoption of AI in banking sector. Previous literature mainly focuses on the general effects of AI in enterprises. 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 irresponsible green finance is due to information asymmetry, while AI can uncover more data and information. This bridges the two conceptions. Therefore, in this paper, we aim to fill the research gap by discussing the characteristics of AI and its effects on responsible green finance.

2.3 Hypothesis Development: Decoupling of Green Finance and Re-coupling of AI

As discussed, the issue of irresponsible green finance arises because of the decoupled information accepted by financial institutions. This 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. Environmental decoupling in disclosure is a representative embodiment of advantaged information. Firms publishing decoupled environmental information not only cater to environmental regulations and acquire institutional benefits (Li et al. 2023), but also confuse financial institutions' judgement when firms apply for financing. Thus, we show such irresponsible problems arise from financial institutions' decoupling because they deviate from the expectation of green finance. This aggravates the scope and negative effect of the conception of decoupling (Birindelli et al. 2024; Wu and Shen 2013).

Based on information asymmetry between firms, financial institutions, and regulators, we suggest that irresponsible green finance has two decoupling mechanisms for financial institutions. First, financial institutions may make irresponsible and risky decisions from a market-based perspective (Xing et al., 2021). As an example, corporate environmental decoupling confuses banks. They may consider that such decoupling is concrete environmental performance and beneficial for firms. In reality, firms' environmental decoupling is risky and harmful to financial performance in the future, triggering higher solvency risks to firms' creditors such as banks (Aintablian et al. 2007; Wu et al. 2023). This can be described as a mechanism of "risk identification decoupling". Second, as green finance is largely driven by policymakers, financial institutions may misunderstand green finance policy (Zhang 2022). They may deem that decoupled information has substantially conformed to regulations, while being essentially contrary to them. When firms' environmental decoupling is detected by regulators, financial institutions may also be punished because they are regarded as supporters of these enterprises (Finger et al., 2018). This mechanism can be defined as "legitimacy decoupling". The dual decoupling mechanisms of financial institutions go together. The problem of irresponsible green finance can be solved only when financial institutions can escape from these two decoupling mechanisms. This requires them to have stronger information recognition capabilities, i.e., mitigating environmental information asymmetry. In this case, AI can play a significant role if financial institutions adopt it.

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[3]. 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. This is useful to appraise corporate environmental information.

Second, automation can solve the low-efficiency problem of information acquisition and analysis. 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). As discussed, corporate environmental information and the evidence of environmental decoupling is scattered. Firms' stakeholders usually pay too much to acquire such information. They 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-

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

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 corporate environmental information and decoupling.

Based on the characteristics of AI, the problem of irresponsible green finance can be solved. We propose that AI can assist financial institutions to escape from dual decoupling mechanisms of risk identification and legitimacy, and achieve re-coupling. First, in risk identification re-coupling, financial institutions 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. Financial institutions are more able to identify which information may be manipulated and increase risks. This means that AI improves financial institutions' risk control abilities. They can make more rational decisions for hedging solvency risks and mitigating future financial impacts. For instance, banks can charge higher interest spreads for suspected firms' decoupled information when they grant loans. Besides, the automation underpinning AI leads conclusions from the analysis to be more stable and accurate than if undertaken by humans. The adoption of AI can simultaneously achieve the aims of rapid review and risk control.

Second, in legitimacy re-coupling, AI builds a foundation to match corporate information with regulations and policies. Besides the financial impact, financial institutions are also concerned with legitimacy. In green finance, any behaviour opposing environmental policies and regulations is risky and liable to be punished. However, friction between green finance practices and regulations exists because financial institutions have limited ability to compare corporate environmental information with policies, leading to legitimacy obstacles. AI systems of financial institutions, by standardization, can advise whether enterprises' 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 companies[4]. In combination with standardized enterprise information, corporate decoupled information will be considered as a contradiction. In this process, AI plays a role to improve financial institutions' legal compliance. At the same time, AI's automation strengthens the efficiency of the comparison. Similarly, as previous literature shows that more institutionally compliant financial institutions are more likely to require stricter financing conditions (Granja and Leuz, 2024), we can infer that firms with a higher degree of environmental decoupling cannot acquire preferential financing, e.g., banks may increase financing costs and specify supplementary conditions to limit the use of loans.

Above all, we suggest that AI can achieve dual re-coupling of risk identification and legitimacy of financial institutions, improve their abilities at risk control and legitimacy, and help them better detect decoupled environmental information. Therefore, financial institutions with AI can make rational financing decisions to correct the use of misleading information in green finance. Accordingly, we propose the following hypothesis:

H: When financial institutions adopt AI, the financing conditions for firms with higher degrees of environmental decoupling in information will be stricter.

3 Methodology

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

3.1 Data

Bank loans are the main embodiment of green finance in China. Thus, 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 Chinese business banks (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 decoupling 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 conditions. 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. Financial institutions (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 (ir)responsible green finance and 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 (Figure 1 is an example). 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 (such as ICBC) achieving level 3.

The second explanatory variable is the degree of corporate environmental decoupling, for which we use notation *EDD_firm*. This variable measures misleading claims of green finance in combination with the dependent variable, based on previous literature on corporate greenwashing and environmental decoupling 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 decoupled environmental disclosure as the disparity between symbolic and substantial environmental information, *EDD_firm* equals the ratio of symbolic information minus the ratio of substantial information. We then standardized this variable. When *EDD_firm* equals 0, the firm has lowest decoupling degree of environmental disclosure, while a higher value of

EDD_firm indicates severe environmental decoupling.

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[5]; 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 (*Syndicate_loan*) which equals 1 if the loan is syndicated[6]; 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

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[5] 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).

[6] 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.

(*Credit_bank*) which is a graded variable ranging from 1 to 5[7]; 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.

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 irresponsible green finance. We expect that the coefficient of *EDD_firm* (β_1) is negative, meaning that firms with a higher degree of environmental decoupling can obtain preferential loan contracts. This is contrary to the original design of green finance. In Eq.2, we added the interaction of AI, i.e., *AIStrategy_bank×EDD_firm* and *AILevel_bank×EDD_firm*. They are the focus of our research and can test the

[7] 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.

hypothesis. We expect their coefficients (β_0) to be significantly positive, suggesting that bank's AI can mitigate the effect of environmental decoupling 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% of the loan contracts in our sample are mortgages and 15.9% of 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 decoupling. We classified the firms whose values of *EDD_firm* are larger than the median in the current year into the higher group[8]. We find that higher degrees of environmental decoupling are more prevalent in SOEs and enterprises 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 decoupling degrees can be found for large amount loans, mortgage loans, and non-syndicated loans.

[Insert Table 1 about here]

4 Results

4.1 Baseline Results

4.1.1 Validation of Irresponsible Green Finance

We first test the existence of irresponsible green finance using regression Eq.1 which is a prerequisite for the hypothesis test. As only higher degrees of environmental

[8] 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.

decoupling 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 decoupling can help firms acquire lower loan spread as the coefficients of *EDD_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 *EDD_firm*'s economic significance is 0.216[9], implying that when firms improve degrees of environmental decoupling 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 *Size_firm*, *PPE_firm*, *Cash_firm*, and *SOE_firm* are significantly negative, indicating that larger firms, stated-owned firms, and enterprises 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

[9] 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.

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 on Responsible Green Finance

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 decoupling. According to the first two columns, the coefficients of both *AIStrategy_bank×EDD_firm* ($\beta = 4.110$, $p < 0.01$) and *AILevel_bank×EDD_firm* ($\beta = 2.739$, $p < 0.01$) are positive at the 1% levels. Correspondingly, the coefficient of *EDD_firm* is insignificant in column (3) for banks that have adopted AI ($\beta = -2.129$, $p > 0.1$), whereas it is significant in column (4) and similar to the results of Table 2 ($\beta = -10.052$, $p < 0.01$). These suggest that banks' AI will drive responsible green finance as firms with decoupled environmental disclosure cannot obtain preferential loan contracts. Therefore, our findings are supportive of the hypothesis (H).

[Insert Table 3 about here]

4.2 Heterogeneities of AI

The baseline results confirmed the capability of AI in detecting environmental decoupling. However, the conception of AI is inclusive. This allows us to further explore the differences between various AI patterns. In this paper, we analyse AI from three different aspects. First, we consider the development trend of AI and compare large-model and conventional AI. Second, we consider the implementation scope of AI and compare internal and bilateral AI. Finally, we consider the establishment type of AI and compare open-source and closed-source AI.

4.2.1 Large-model AI vs. Conventional AI

Large-model AI is emerging in recent years. Its prominent application is generative AI such as ChatGPT. Conventional AI is usually based on limited training samples and its capabilities are subject to the scope of training materials (Luitse and Denkena, 2021). It usually only shows the predetermined results but these may be biased and useless, especially if the training process is detective. Such AI can be hard to automatically update, resulting in obsolete solutions, particularly for decoupled environmental information. Large-model AI is generative and based on more advanced technologies such as convolutional neural network, big data, and supercomputing power (Liu et al. 2022). By iterative algorithms that are theoretically infinite, large-model AI can give more comprehensive, reasonable and contemporary results (Luitse and Denkena, 2021). Accordingly, we conjecture that large-model AI is more effective than conventional AI in detecting environmental decoupling and cultivating responsible green finance.

We built two dummy variables to measure these two AI types. First, we oriented the keywords of “large-mode” and “generative” and searched for them among the raw materials of annual reports, official websites, media coverage, etc. If we find a bank implemented large-model AI, the variable *LMAI_bank* equals 1, and 0 otherwise 0[10]. If a bank only implemented conventional AI, we assigned the value of variable *ConAI_bank* as 1, and 0 otherwise. We added two interactions (*LMAI_bank×EDD_firm* and *ConAI_bank×EDD_firm*) into the regression model. The results are shown in Table 4, column (1). It illustrates that large-model AI is more useful to address irresponsible green finance, as the coefficient of *LMAI_bank×EDD_firm* is significantly positive ($\beta = 8.008$, $p < 0.01$) but that of *ConAI_bank×EDD_firm* ($\beta = 2.431$, $p > 0.1$) becomes insignificant. The F-test for the difference is also significant at the 1% level. This supports our inference that large-model AI is more effective to reduce the effect of environmental decoupling.

4.2.2 Internal AI vs. Bilateral AI

Internal AI refers to AI systems that can be only used by banks' staff or decision makers, while bilateral AI is also open to clients. In bilateral AI, users and clients can usually acquire updates, upload information, develop questions, and make other interactive activities with banks on AI platforms. Although the AI interfaces and functions are distinct for staff and clients, it provides more information access. For instance, bilateral AI can collect more client information and analyse the trend of client preferences. These are helpful for banks' new strategies and correct decisions, and useful for acquiring more knowledge of environmental decoupling. Correspondingly, internal AI may be less efficient in detecting environmental disclosure decoupling because it loses many channels that recognize it. We thus infer that bilateral AI is better than internal AI in mitigating irresponsible green finance.

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[10] We assume that banks will publicize the large-model AI adoption if they adopted it. Self-developed large-model AI and purchased large-model AI are included, and the latter is dominant.

We visited all sample banks' official websites and mobile applications to record whether they have bilateral AI systems or platforms. Typical external AI systems for clients include intelligent consultants, intelligent interactive platforms, automatic loan application systems, etc. We also check their reports and news to identify the online availability of such AI systems. We defined banks implementing AI without bilateral AI as internal AI. Thus, the first variable is *IntAI_bank*, which equals 1 if a bank only has internal AI systems. The second variable, *BiAI_bank*, equals 1 if a bank employs bilateral AI systems. The comparison result is shown in Table 4, column (2). We find that the coefficient of *BiAI_bank×EDD_firm* (β = 6.836, $p < 0.01$) is significantly greater than that of *IntAI_bank×EDD_firm* (β = -0.471, $p > 0.1$), with the difference confirmed by the F-test. These suggest that bilateral AI can better drive responsible green finance in bank lending.

4.2.3 Open-source AI vs. Closed-source AI

Open-source is regarded as an innovation in software development. Individuals and organizations can acquire basic elements to develop new software systems (Ebert and Louridas, 2023). In contrast, closed-source means that the new software is developed by original elements and techniques. Open-source is common in the development of AI systems. For example, OpenAI, which is the creator of ChatGPT, was open-sourced before the departure of Elon Musk. Open-source AI is defined as the AI systems built by open-source approaches. As many open-source resources (code, techniques, etc.) can be adopted, open-source AI is less constrained by resources and has advantages in system update (Pearce and Mushtaq, 2009). Such AI is more flexible to design, and more complete in use. Thus, we conjecture that open-source AI is more capable of following the development of environmental protection and can better learn about environmental decoupling behaviour. We expect that open-source AI is more likely to achieve responsible green finance.

We collected evidence of banks' open-source AI from banks' reports, websites, media coverage, etc. According to open-source conventions, any product totally or partially developed by open-sourced resources should be disclosed. This accelerates our data collection process. We defined the first variable *OSAI_bank,* which equals 1 if the AI system uses open-source resources, and the second variable *CSAI_bank*, which equals 1 if the AI system does not indicate use of open-source. The results are shown in Table 4, column (3). The coefficient of *OSAI_bank×EDD_firm* is significantly positive (β = 7.705, p < 0.01). Although the interaction *CSAI_bank×EDD_firm* is marginally significant (β = 2.886, p < 0.1), the F- test suggests that they are significantly different. Thus, we can conclude that open-source AI can better mitigate the impact of environmental decoupling on loan financing.

[Insert Table 4 about here]

4.3 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 finance, 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 finance while others do not. These can also change the effect of AI on (ir)responsible green finance.

4.3.1 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 enterprises are more obvious for bank environmental review. Their environmental information decoupling 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 decoupled environmental disclosure 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 5. 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 *EDD_firm* in the polluting firm group are meaningful even though they are insignificant. They imply that polluting firms cannot obtain preferential loan contracts with decoupled environmental information, showing that firms' polluting image will trigger banks' caution in granting loans.

[Insert Table 5 about here]

4.3.2 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 finance 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 decoupled. 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 decoupling in disclosure, 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 6. 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); β = 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 irresponsible green finance, especially in banks with more green experience.

[Insert Table 6 about here]

4.4 Channel Analyses

In hypothesis development, we narrated two re-coupling channels of AI, namely, risk identification capability and legitimacy. The former means that banks with AI can better detect decoupled 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 responsible green finance achieved by AI.

4.4.1 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 finance development, we expect that AI can reduce NPL ratio, and the irresponsible relationship between environmental information decoupling 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.

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

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

The results of the channel of risk identification are presented in Table 7, 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 their 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 decoupling (*rNPLS_bank×EDD_firm* and *rNPLL_bank×EDD_firm*) are also significantly positive ($\beta = 10.582$, $p < 0.05$ in column (3); $\beta = 12.041$, $p < 0.05$ in column (4)). Such results support banks' AI adoption mitigating irresponsible green finance by the channel of risk identification re-coupling.

[Insert Table 7 about here]

4.4.2 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 finance, AI can further reduce the degree of legitimacy decoupling, and help banks make correct decisions in line with the institutions and legitimacy on reviewing corporate environmental decoupling in disclosure. Finally, the irresponsible green finance 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 8. 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×EDD_firm* and *rPenaltyL_bank×EDD_firm* are also significantly positive (β = 3.861, p < 0.01 in column (3); β = 4.893, p < 0.01 in column (4)). Such results confirm the channel of legitimacy re-coupling.

[Insert Table 8 about here]

4.5 Endogeneity Tests and Robustness Checks

4.5.1 Considering Reverse Causality

In the baseline analysis, we show that corporate environmental decoupling can reduce loan spread, and banks' AI can mitigate this relationship. We attribute such effects to AI's capability in driving responsible green finance. 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 decoupling 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., *EDD_region*, *AIStrategy_region*, *AILevel_region*). Specifically, we calculate the average degrees of corporate environmental decoupling 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 (*EDD_firm*, *AIStrategy_bank*, *AILevel_bank*) as dependent variables and use corresponding IVs (macro variable) as independent variables to calculate fitted values (*hatEDD_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 9, 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 9 about here]

4.5.2 Considering the Bias of Environmental Decoupling

We further consider the endogeneity problem of sample bias. The first type of bias is from corporate environmental decoupling. Many firm characteristics are significantly different between firms with higher and lower degrees of decoupling. Our baseline results may result from such differences instead of environmental decoupling in disclosure. 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 decoupling[11], and select firm characteristics shown in the variable section as the covariates. The results are shown in Table 10. Panel A suggests that the differences 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 10 about here]

4.5.3 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 11 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 11 about here]

4.5.4 Sample of Survey Data

Our sample of baseline analysis is based on the listed firms' loan contract data.

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

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 enterprises. Second, compared with listed firms, small enterprises' 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 enterprise 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 enterprise'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 enterprise acquires a bank loan? (1 to 7)

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

Q: Did your enterprise 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 enterprise 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 decoupling (*EDD*). 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 has long-term cooperation with the bank), and *IND* (industry effects).

The results from using the alternative survey data are shown in Table 12. The coefficient of *EDD* is significantly positive (β = 0.170, $p < 0.05$ in column (1); β = 0.187, $p < 0.05$ in column (2)), suggesting that SMEs with higher environmental decoupling degrees are more likely to acquire loans. Nevertheless, the interactions are both significantly negative (β = -0.258, $p < 0.01$ in column (1); β = -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 12 about here]

5 Discussion and Conclusions

5.1 Concluding Remarks

In this paper, we discuss an irresponsible phenomenon of green finance and the role of AI in mitigating it. Based on 1209 loan contracts from 2019 to 2023, we find that corporate environmental decoupling can help firms acquire loans with lower interest spreads (reflecting irresponsible green finance issue), whereas banks' AI adoption can mitigate this influence. Based on information asymmetry theory, we attribute these findings to the decoupling process of manipulated information and the re-coupling effect of AI. We find that in the context of green finance, banks' AI systems can better identify the decoupled information in standardized and automatic ways. These strengthen the risk identification capability and legitimacy of banks, and we demonstrated these two re-coupling channels. We also explored the boundaries of AI's effect. We find that large-model AI, bilateral AI, and open-source AI are more effective in cultivating responsible green finance because these types of AI are more targeted and sophisticated in reviewing information. Finally, AI-driven responsible green finance 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 decoupled means to obtain green finance resources to which they are not entitled, financial institutions 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 of (ir)responsible green finance 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 "decoupling and re-coupling" view of (ir)responsible green finance 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 is multidisciplinary and easily manipulated. This leads to environmental decoupling (Crilly et al., 2012). Although studies have explained environmental decoupling 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 decoupling process triggered by asymmetric information in combination with the behaviours and motivations of firms and financial institutions, such as risk identification decoupling and legitimacy decoupling. Then, we show that appropriate instruments (e.g., AI) can achieve re-coupling when they 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, financial institutions, and enterprises. Firstly, as we emphasize the re-coupling effect of AI, government departments can drive a responsible green finance market from supply and demand perspectives. In the financing supply side, governments can carry out relative guidelines to encourage financial institutions' adoptions of AI systems, especially those with higher iteration capabilities such as open-source AI and generative AI. In the financing demand side, governments can implement AI-supported environmental institutions to control decoupling behaviours. For instance, intelligent environmental assurance is feasible to improve information quality.

Secondly, this paper helps financial institutions exclude "AI concerns" and can motivate them to construct efficient AI systems, especially in the trend of green finance. 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, financial institutions 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 decoupling and other manipulated information become redundant with the development of digital technologies. Enterprises 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 decoupled information 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 irresponsible green finance 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 decoupled environmental information, 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 finance 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 finance, or environmental decoupling.

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
EDD_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***
EDD_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 Decoupling in Disclosure

Variables	Firms with Lower Environmental Decoupling		Firms with Higher Environmental Decoupling		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. Results of Irresponsible Green Finance

	(1)	(2)
	Spread_loan	*Spread_loan*
EDD_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 on Irresponsible Green Finance

	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	No-AI Sample	AI Sample
	Spread_loan	*Spread_loan*	*Spread_loan*	*Spread_loan*
EDD_firm×AIStrategy_bank	4.108^{***}			
	(3.07)			
EDD_firm×AILevel_bank		2.739^{***}		
		(4.49)		
EDD_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. Results of the Heterogeneities of AI

	(1)	(2)	(3)
	Spread_loan	*Spread_loan*	*Spread_loan*
EDD_firm×LMAI_bank	8.008***		
	(4.83)		
EDD_firm×ConAI_bank	2.431		
	(1.39)		
EDD_firm×IntAI_bank		-0.471	
		(-0.22)	
EDD_firm×BiAI_bank		6.837***	
		(4.66)	
EDD_firm×OSAI_bank			7.705***
			(4.40)
EDD_firm×CSAI_bank			2.886*
			(1.93)
EDD_firm	-5.849***	-5.784***	-5.768***
	(-4.15)	(-4.18)	(-4.04)
LMAI_bank	-0.599***		
	(-3.89)		
ConAI_bank	-0.383***		
	(-2.83)		
IntAI_bank		-0.511***	
		(-3.61)	
BiAI_bank		-0.489***	
		(-3.32)	
OSAI_bank			-0.613***
			(-4.46)
CSAI_bank			-0.220
			(-1.54)
Control Variables	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Constant	-17.456***	-17.652***	-15.201**
	(-2.73)	(-2.72)	(-2.36)
N	1209	1209	1209
Adj. R^2	0.557	0.559	0.560
F-test for Difference	7.40***	9.47***	6.82***

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 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*
EDD_firm×AIStrategy_bank	0.779	5.522***		
	(0.36)	(2.99)		
EDD_firm×AILevel_bank			-0.233	3.440***
			(-0.33)	(4.08)
EDD_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 6. 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*
EDD_firm×AIStrategy_bank	19.617***	4.986***		
	(3.52)	(2.90)		
EDD_firm×AILevel_bank			7.203***	3.501***
			(4.04)	(3.54)
EDD_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 7. Results of the Risk Identification Re-coupling Channel

	(1)	(2)	(3)	(4)
	rNPL_bank	*rNPL_bank*	*Spread_loan*	*Spread_loan*
AIStrategy_bank	0.096***			
	(8.94)			
AILevel_bank		0.047***		
		(10.30)		
rNPLS_bank×EDD_firm			10.582**	
			(2.00)	
rNPLL_bank×EDD_firm				12.041**
				(2.35)
EDD_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 8. Results of the Legitimacy Re-coupling Channel

	(1) *rPenalty_bank*	(2) *rPenalty_bank*	(3) *Spread_loan*	(4) *Spread_loan*
AIStrategy_bank	0.343^{***}			
	(5.52)			
AILevel_bank		0.223^{***}		
		(7.22)		
rPenaltyS_bank×EDD_firm			3.861^{***}	
			(2.60)	
rPenaltyL_bank×EDD_firm				4.893^{***}
				(3.36)
EDD_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 9. Results of Instrumental Variables

	First-stage			Second-stage: 2SLS		Second-stage: GMM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	EDD_firm	*AIStrategy_bank*	*AILevel_bank*	*Spread_loan*	*Spread_loan*	*Spread_loan*	*Spread_loan*
EDD_region	0.754***						
	(14.25)						
AIStrategy_region		0.874***					
		(36.69)					
AILevel_region			0.911***				
			(41.11)				
hatEDD_firm×hatAIStrategy_bank				3.273**		50.866**	
				(1.99)		(2.03)	
hatEDD_firm×hatAILevel_bank					2.519***		17.769*
					(3.01)		(1.92)
hatEDD_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 10. Entropy Matched Results of Firm Characteristics

Panel A. Mean Values before and after Match

Matching Variables	High Environmental Decoupling	Low Environmental Decoupling	
		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*
EDD_firm×AIStrategy_bank	3.560^{**}	
	(2.20)	
EDD_firm×AILevel_bank		2.998^{***}
		(4.25)
EDD_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 11. 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*
EDD_firm×AIStrategy_bank	5.972^{***}	
	(4.38)	
EDD_firm×AILevel_bank		3.459^{***}
		(5.90)
EDD_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 12. Results of Survey Data

	(1)	(2)
	Loan	*Loan*
EDD×AIStrategy_bank	-0.529***	
	(-3.29)	
EDD×AILevel_bank		-0.258***
		(-3.41)
EDD	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).

Figures

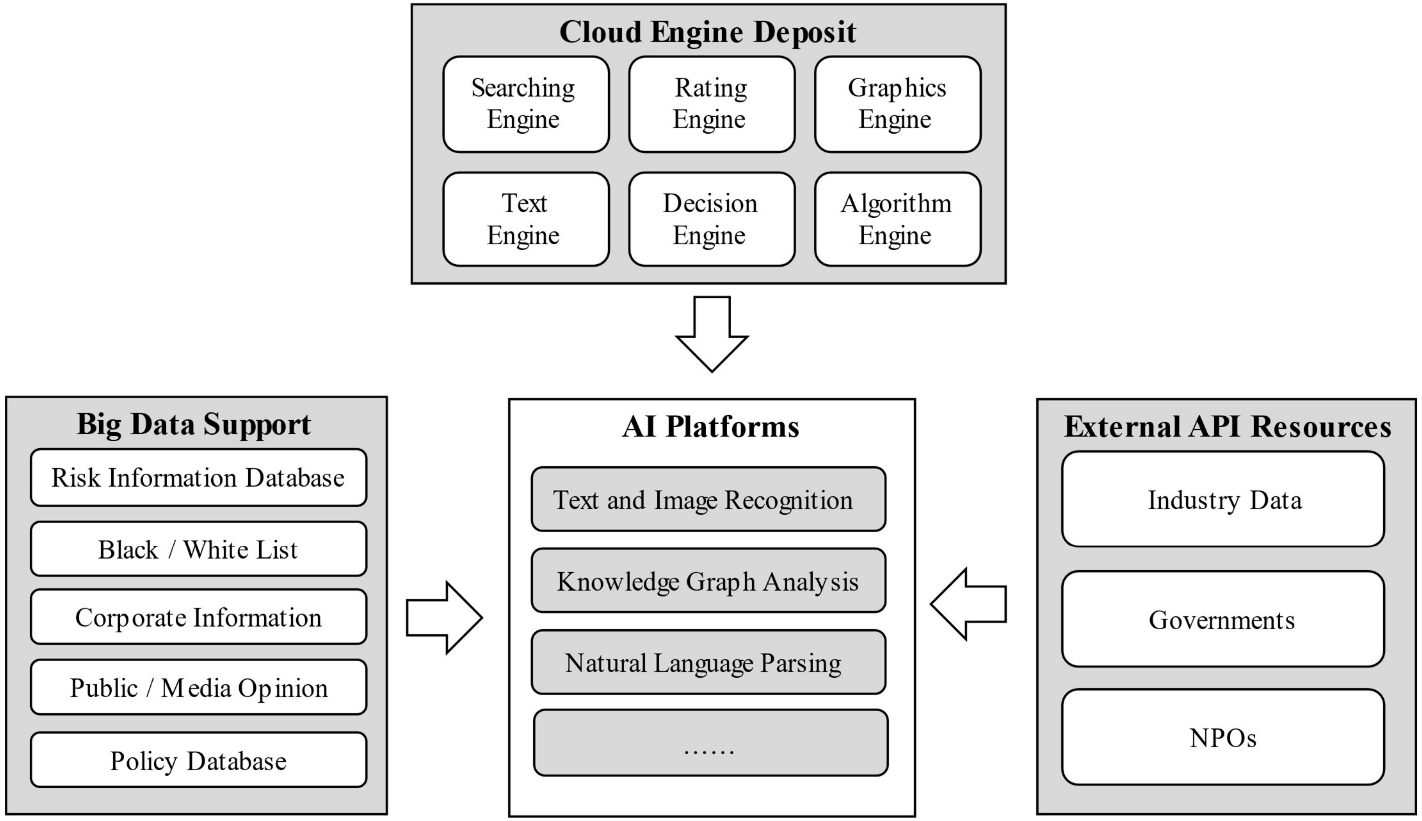

Figure 1. AI Adoption of ICBC

Appendix A. Measurement of Environmental Decoupling in Disclosure

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 decoupling degree in corporate environmental disclosure.

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 decoupling. According to Walker and Wan (2012), environmental decoupling 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 decoupling to total environmental decoupling.

The procedure of the measurement is shown in Figure A1.

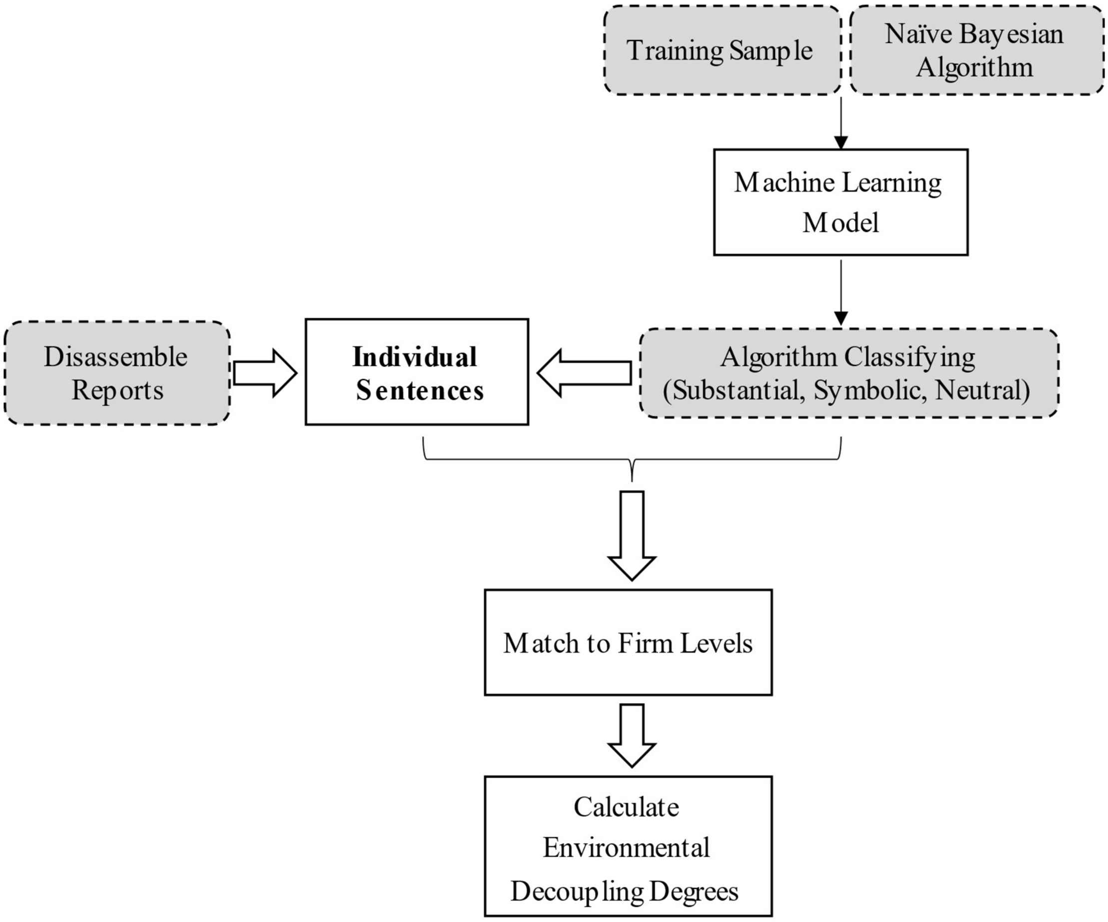

Figure A1. Measurement Procedure of Environmental Decoupling

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 decoupling	*EDD_firm*	Environmental decoupling 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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