Levels of AI Investment, Environmental Disclosure Performance, and Firms' Interest-Bearing Debt Financing Levels

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Abstract. Due to the broad use of artificial intelligence (AI) technologies in enterprises' operations, an issue arises regarding the influence of AI investments on the financing behavior of firms. In this study, a sample of Chinese A-share listed firms from 2010 to 2023 was used to empirically investigate the influence of AI investment levels on interest-bearing debt ratios of firms, as well as to test the role of environmental disclosure performance in this regard. The results show that there exists a strong positive relationship between AI investment levels and interest-bearing debt ratios, which might mean either a high propensity to finance through debt or higher interest-bearing debts of firms. According to the results of stepwise regression, it can be concluded that AI investments are negatively related to environmental disclosure performance, and environmental disclosure performance is negatively correlated with interest-bearing debt ratios of firms, suggesting resource trade-offs. Heterogeneity analysis shows that this effect is mainly valid for large-scale firms, and robustness tests confirm the main results of this paper.

Keywords: AI investment level, Environmental disclosure performance, Level of interest-bearing debt financing, Interest-bearing debt ratio, debt financing

1. Introduction

Technological advancement such as AI is changing how organizations manufacture, strategize, and invest their resources. In recent times, the amount invested by Chinese companies that are listed in the AI industry has been growing bigger and bigger. From the information given by IT Juzi, the total amount of investment in China's AI industry surpassed the total amount of investment made in the year 2025 in only half a year, where in the first half of 2026, the total investment was above 300 billion yuan, with the AI investment being 48.6 percent of the total amount of primary market investment. This means that AI is now not only a technology but it is becoming part and parcel of organizational strategies and financial management.

The literature on AI mostly pays attention to the effects of AI on the improvement of labor efficiency, innovation production, and governance efficiency, and the key reasoning behind this is that AI can be considered a technology that helps increase corporate efficiency. Nevertheless, this approach fails to explain in what way AI investments influence firms' borrowing behavior. AI investments require significant capital expenditure and changes in the structure of the resources used by the company, which can lead to changes in the amount of debt financing in terms of two channels: signaling and crowding out effect. Existing research has failed to combine the issue of AI investments with the interest burden ratio.

This paper posits that investment in AI technology might convey information about technology upgrades and thus increase the confidence of outside capital providers regarding the firm's future growth, affecting the interest-bearing debt ratio, which can be seen as an indication of the firm's ability to finance itself externally. At the same time, investment in AI technology involves considerable resource investment and might, in the short run, detract the firm's attention from environmental information disclosure management, causing a resource trade-off. This paper investigates, using a sample of A-share listed firms in China from 2010 to 2023, the effect of AI investment level on firms' interest-bearing debt ratio and the effect of environmental disclosure performance on this relation.

The marginal contributions of this study can be illustrated from the following three perspectives: First, by relating AI investment to corporate debt financing practices, the study contributes to the research boundary of economic implications of AI; second, by showing resource trade-off between AI investment and ESG management, the study provides a new insight into corporate resource management; third, the study discovers different financing effects of AI investment on different firms.

2. Literature Review and Research Hypotheses

2.1. Literature Review

2.1.1. Research on the Application of AI Technology

AI is revolutionizing the production process and governance structures of enterprises. While digital transformation involves efficiency enhancement through the use of information technology, AI is based on learning from the data, recognizing patterns, and automated decision-making. Real-time processing of large amounts of data changes the decision-making processes and resource allocation mechanisms in enterprises (Jin et al., 2024). [1, 3, 11]Measurement is concerned with the existing literature that offers guidance in identifying the use of AI technology in enterprises.

In terms of the actual effects of AI on firms, previous studies have provided support from different angles. Li et al. (2026) calculated the degree of AI utilization in enterprises by giving weights to the level of AI penetration at the occupation level, [5]considering the employment structure, using A-share listed firms' data in 2015–2024. AI lowers the effective income tax rate of firms via three routes: salary tax deductions, debt tax shields, and better internal control quality. Internal control quality improvement means the enhancement of information transparency and governance efficiency, and this is an important institutional base for better corporate environmental disclosures (Hu et al., 2023).[9, 12, 14] It can be seen that the effect of AI goes beyond production activities to impact firm governance and financial management. Such results show that, through better information transparency and governance quality, AI may have an effect on firm debt financing capability, providing the theoretical basis for this study.

Most previous papers have studied the enabling effect of AI when AI has reached maturity in its usage from a long-term perspective, but this study has chosen to study the resource crowding-out effects that will occur when businesses make concentrated AI investments within the short term. With the different time frames that have been used in these papers, both the enabling effect in the long term and the crowding-out effect in the short term can be observed together without having any logical conflicts. Thus, the hypothesis of this study does not conflict with the positive findings in the existing literature.

Concerning the linkage between AI and environmental disclosure performance, there is scarce evidence available. In an empirical study conducted by Yuan et al. (2026)[10], using the data of manufacturing companies between 2010 and 2024, the results reveal that digital and intelligent transformation (including AI, big data, cloud computing, and blockchain) has a significantly positive effect on the environmental disclosure performance of firms, and the green business philosophy makes the effect more pronounced.[22, 25, 39] Also, Wang and Zhang (2024) [21]concluded that digital transformation improves the environmental performance of corporations, and artificial intelligence, big data, and cloud computing have a significant effect in this regard. Mechanistically speaking, the environmental disclosure performance enhancement with AI can occur in three aspects: environmental aspect through improving the accuracy of monitoring and energy consumption management; social aspect through better risk management of the supply chain and employee management; and the governance aspect through better internal controls and information transparency.

Synthesizing the above literature, existing research preliminarily indicates that AI has a positive impact on environmental disclosure performance and has identified potential mechanisms such as internal controls and information transparency. However, most of these studies examine the enabling effects of AI from a long-term perspective, whereas this paper focuses on short-term resource

crowding out and resource trade-offs; the difference in focus between the two is not contradictory but stems from different observation windows.

However, there is limited academic research on the use of AI as an independent technology rather than being part of a wider digital transformation. Measuring the implementation of AI through keywords from the annual report is a case of operational bias, as some firms might mention AI in their annual reports even though they have not implemented the technology. When considering the impact of AI on the use of debt financing in relation to environmental disclosure performance, there has been little consideration of AI technology adoption, environmental disclosure performance, and green credit institutionality within one connected study framework.

2.1.2. Research on Environmental Disclosure Performance

Discussion on the effects of environmental disclosure performance on corporate financing has been made widely. The theories behind it include stakeholder theory, signaling theory, information asymmetry theory, and legitimacy theory. It is necessary for organizations to be responsive to the needs of all their stakeholders. In addition, environmental disclosure performance is an indicator that helps convey risk information to the external world (Fang & Hu, 2023)[2, 8, 15], which not only mitigates information asymmetry but also helps firms gain institutional legitimacy through reducing credit premiums (Hu et al., 2023; Si & Cao, 2022).[14, 23] Environmental disclosure performance may have some impact on the interest-bearing debt ratio and interest-bearing debt financing of a firm; however, they are different variables.

With respect to the interest-bearing debt ratio, studies have shown fairly consistent results. According to Wang and Yang (2022)[24], better environmental disclosure performance increases the value of the company by reducing the interest-bearing debt ratio. According to Hu et al. (2023)[14], taking advantage of the exogenous shock due to the initial publication of environmental disclosure performance information from Shangdao Ronglv, it is shown that environmental disclosure performance can alleviate financing constraints, thus indirectly making it easier for companies to get financing. Nonetheless, the above-mentioned literature mainly examines the interest-bearing liabilities to interest-bearing liabilities ratio or the interest-bearing liabilities to equity ratio, which differs from the interest-bearing debt ratio used in this study in terms of variable attributes. Although this paper has not conducted any empirical research on the interest-bearing debt ratio, based on the mechanisms of information transparency and risk signals found in the above literature, environmental disclosure performance could improve the information environment of the company, which would affect the bank credit decision-making and the quantity and structure of debt financing of the company.

Also, the financial impacts of environmental disclosure performance will be magnified by green credit programs. Si and Cao (2022) have proven that the "Green Credit Guidelines" issued in 2012 improved the environmental and social responsibilities of companies in two respects: firstly, external pressure (cost increase of financing and narrowed financing channels); and secondly, internal attention (promotion of enterprises' awareness of environmental responsibilities). Li et al. (2026)[15] have proved that good environmental disclosure performance could decrease supplier and customer concentration, strengthen the resilience of the supply chain and thus improve the green innovation performance.[31, 40, 41]

It has been proved by previous literature that the interest-bearing debt financing ratio can be decreased by good environmental disclosure performance. The mechanism of information transparency and internal control has been identified, while the green credit system is able to magnify the impact of good environmental disclosure performance. But most previous literature treats environmental disclosure performance as an endogenous signal, rarely considering its drivers and hardly analyzing how the relationship between environmental disclosure performance and interest-bearing debt financing is formed.[19, 20, 29, 33]

2.1.3. Research on the Relationship Between Green Credit and the Interest-Bearing Debt Ratio

The translation of environmental disclosure performance into an advantage in the interest-bearing debt ratio has to be viewed through the lens of institutional logic in green credit. In 2012, the issuance of the "Green Credit Guidelines" made it obligatory for banks to take into account environmental and social risk factors of clients when approving credits and determining their rates (Si & Cao, 2022)[23]. Different from other environmental regulations, green credit is not about penalties; instead, it works by means of financial resource redistribution: first, it makes it harder for polluting firms to obtain loans and increases their loan interest rates; second, green firms can receive financing (Cui et al., 2023)[7, 16, 18, 27, 36]. The difference between green credit and the interest-bearing debt ratio should be clarified because green credit is a credit policy affecting the interest-bearing debt ratio of bank loans of enterprises, while the interest-bearing debt ratio covers other kinds of debt, including bonds. Given the limited availability of data, the interest-bearing debt ratio will serve as a proxy variable in assessing its changes in the green credit context.

When considering the micro-level impacts of green credit, many empirical studies have been carried out. With respect to financing, the green credit policy does have an impact on raising the difficulties and costs of financing for heavily polluting companies, making the size of debt financing decrease (Cui et al., 2023)[16, 18]. When considering the behavior of companies, green credit may encourage enterprises to make more environmental investment and enhance their environmental and social responsibilities (Si & Cao, 2022)[6, 13, 23, 42]. In the game theoretical analysis conducted by Zhou et al. (2023)[46, 30], green credit encourages heavily polluting companies to conduct green technological innovations, and the outcome is only a rise in quantity (utility model patents) while the quality (invention patents) remains relatively stable.

As far as the measurement of the interest-bearing debt ratio is concerned, there is already enough literature that can give us some relevant measures to refer to. “Financial expenses/total liabilities” was adopted by Wang & Yang (2022)[24], whereas the study by Qiu et al. (2024) [4]used some variables related to interest expenses. All studies lack data about green loan interest rate at the firm level, so they define the dependent variable as cost of debt financing or cost of bank credit financing, taking green credit as an institutional setting (Guo et al., 2024)[7, 16]. Since this paper takes interest-bearing debt ratio as its measure, the dependent variable is taken as the amount of a firm’s interest-bearing debt financing.

In conclusion, past literature has shown how the structure of green credit has an effect on finance cost and the methods of measuring such impact. However, past studies tend to consider the impact of green credit policy without giving much consideration to the impact that a firm’s features may have. The main line of thinking in this research is different from other existing literature since past studies have considered the long-term enabling impact of AI on environmental disclosure performance, while in this study, the short-term crowding-out resource impact of AI investment on firms is investigated by seeing if AI investments have an influence on firms’ interest-bearing debt ratio through environmental disclosure performance.[10, 21]

2.1.4. Literature Review and Research Approach

In conclusion, previous research provides this study with theoretical guidance and empirical support in three aspects. Firstly, AI applications have a positive influence on the performance of environmental disclosures, and AI could also enhance corporate governance and information transparency.[5, 14]However, the existing literature integrates AI into the broader discussion of digital transformation and never distinguishes its unique contribution as an algorithm-based decision-making tool, nor does it make a distinction between the enabling and crowding-out effects of it in the long term and short term, respectively. Secondly, the performance of environmental disclosures is able to decrease the interest-bearing debt to total debt ratio, and the green credit system magnifies this effect. However, the existing research mostly regards environmental disclosure performance as an exogenous variable without studying its antecedent conditions and lacks testing of the intermediate

mechanism "how banks evaluate the improvement of environmental disclosure performance and include it into the credit pricing". Thirdly, green credit policies turn environmental disclosure performance into the basis for loan pricing; however, the existing research mainly focuses on the effects of such policies and ignores the influence of firms' own attributes on the credit pricing. These gaps provide the research opportunity for this paper.

However, current studies face three shortcomings. First, at the variable level, previous research mostly focuses on the concept of "digital transformation," while the impact of AI itself has yet to be isolated. Second, at the mechanism level, although some studies have investigated the connection between AI and environmental disclosure performance, and some have studied the link between environmental disclosure performance and interest-bearing debt ratio, none have studied the relationship between the two aspects, thereby forming the chain: "Investment in AI might lead to a temporary trade-off with resource allocation for environmental disclosure performance and affect the debt structure of firms." Third, at the context level, most studies on interest-bearing debt ratio study general debt costs; yet the way banks incorporate environmental disclosure performance into pricing in the green credit system should also be considered in the chain.

From this perspective, this paper selects Chinese A-share listed firms as its sample and contributes to previous studies in three aspects. Firstly, this study emphasizes the use of artificial intelligence technology instead of digitalization in general. Secondly, this paper employs environmental disclosure performance as a mediating mechanism. Thirdly, this paper analyzes the level of corporate debt financing in terms of green finance and environmental disclosure performance evaluation. This paper also provides some marginal contributions to previous literature as follows. First, this paper pays attention to the independent role of AI. Second, this paper tests the transmission mechanism of environmental disclosure performance. Third, this paper analyzes interest-bearing debt ratio in terms of green credit system.

2.2. Research Hypotheses

Based on the above analysis, this paper proposes the following hypotheses:

H1: The level of AI investment is positively correlated with the level of interest-bearing debt financing; that is, firms with higher levels of AI investment have greater access to credit.

The impact of AI investment on corporate debt financing can be through the following two mechanisms: firstly, the signaling effect, whereby AI investments convey positive signals about the technological upgrading and digitalization of the firm, thereby increasing the confidence of the creditors, such as the bank, about the firm's future growth; and secondly, the information effect, whereby the application of AI systems increases the information-processing ability of the firm, hence lowering the information asymmetry in banks' credit decisions.

H2a: The level of AI investment is negatively correlated with environmental disclosure performance.

H2b: AI investment increases firms' levels of interest-bearing debt financing by reducing environmental disclosure performance.

Previous studies have indicated in a preliminary way that AI plays a positive role in environmental disclosure performance (Yuan et al., 2026; Wang & Zhang, 2024) and revealed the underlying mechanism, such as internal control and information transparency (Li et al., 2026; Hu et al., 2023). Nevertheless, the above literature mainly explores the role of AI in the long term, while this paper considers the role of AI in the short term in terms of resource crowding out and resource trade-offs.

However, there is a tendency among researchers to integrate the use of AI technologies into the larger picture of digital transformation, but few studies have found its independent contribution as a technology that can learn algorithms and make decisions intelligently. Furthermore, measuring AI through keywords in annual reports would be biased because the company could include AI technologies in its annual reports even if it has not applied any. When it comes to examining the influence of AI on the degree of debt financing due to environmental disclosure performance, there are no studies that have tried to connect the three factors (Si & Cao, 2022; Wang & Yang, 2022)[23, 24, 43, 44].

3. Research Design

3.1. Sample and Data

The data sample for the present study consists of Chinese A-share listed companies from 2010 to 2023 and is screened based on the following criteria: (1) Exclusion of listed companies in the financial industry; (2) Exclusion of ST, *ST, and PT stocks; (3) Exclusion of data samples with missing values in the main variable. There are 17,781 observations for company-years in total. In order to exclude single-period firms, the final regression analysis was done with the number of 17,781 observations with the help of the fixed effects method. All continuous variables have been trimmed at 1% and 99%. The data on AI investment was drawn from CSMAR "Artificial Intelligence Investment Levels of Listed Companies"; the data on environmental disclosure performance was drawn from CSMAR "Environmental Disclosure Index"; and financial data was drawn from CSMAR "Financial Indicator Analysis of Listed Companies" and "Balance Sheet".

3.2. Variable Definitions

Table 1 reports the definitions and measurement methods of all variables used in this study, including the dependent variable, the key explanatory variable, the mechanism variable, and the control variables

Table 1. Table of Variable Definitions

Variable Types	Variable Name	Symbol	Measurement Method
Dependent Variables	Interest-Bearing Debt Ratio	Leverage	(Short-term borrowings + Long-term borrowings + Non-current liabilities due within one year) / Total assets
Key Dependent Variables	AI Investment Level	lnAI	ln(1 + AI investment amount)
Mechanism Variables	Environmental Disclosure Performance	EG_Index	Environmental Disclosure Performance (CSMAR-adjusted indicator, EG_Index = (Environmental Disclosure Index + Integrated Environmental and Social Indicator) / 2)
Control Variables	Company Size	Size	Logarithm of total assets
	Profitability	ROA	Net income / Total assets
	Growth Potential	Growth	Revenue growth rate
	Shareholding Concentration	Top1	Largest Shareholder's Ownership Percentage
	Combined Executive and Supervisory Roles	Dual	If the Chairman and General Manager are the same person, enter 1
	Cash Flow	CFO	Cash Flow from Operating Activities / Total Assets
	Institutional Investor Holdings	InstInvestor	Institutional Investors' Ownership Percentage

3.3. Model Specification

Fixed effects for each firm are used to control for time-invariant characteristics of the firms, such as corporate culture, management style, and institutional context in the region where the firm operates. Fixed effects for each year are used to control for macroeconomic shocks to all the firms, like monetary policy, credit policy, and the business cycle. The standard errors are clustered at the firm level to allow for the possibility that the disturbance terms are correlated across observations for the same firm in different years. Moreover, the continuous variables such as Leverage and Growth are truncated at the 1% and 99% levels. The regression model used to test the effect of AI investments on the interest-bearing debt ratio is as follows:

$$Leverage_{it} = \beta_0 + \beta_1 lnAI_{it} + \beta_2 Size_{it} + \beta_3 ROA_{it} + \beta_4 Growth_{it} + \beta_5 Top1_{it} + \beta_6 Dual_{it} + \beta_7 CFO_{it} + \beta_8 InstInvestor_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where Leverage represents a firm's interest-bearing debt ratio, lnAI is the logarithm of the AI investment level, Size denotes firm size (the logarithm of total assets), ROA is return on assets (net income / total assets), Growth is the revenue growth rate, Top1 is the largest shareholder's ownership percentage, Dual is a dummy variable indicating the dual role of the chairman and CEO (set to 1 if the chairman also serves as CEO), and CFO is net cash flow from operating activities / total assets, and InstInvestor is the proportion of shares held by institutional investors. μ_i is the firm-specific fixed effect, λ_t is the year-specific fixed effect, and $\varepsilon\{i, t\}$ is the random error term. Standard errors are clustered at the firm level.

In order to examine the influence of the EG_Index variable in the causal chain between AI investment levels and the interest-bearing debt ratio, the upcoming sections will use a bootstrap test for indirect effects so as not to reach the conclusion about mediation only through two regression coefficients. Hence, this paper additionally considers the following model:

$$EG_Index_{it} = \alpha_0 + \alpha_1 lnAI_{it} + \Sigma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it},$$
$$Leverage_{it} = \gamma_0 + \gamma_1 lnAI_{it} + \gamma_2 EG_Index_{it} + \Sigma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

4. Empirical Results

4.1. Descriptive Statistics

Table 2. Descriptive Statistics

Variable	Sample Size	Mean	Standard Deviation	Min	Median	Max
Leverage	17,781	0.2010	0.1431	0.0000	0.1865	0.6219
lnAI	17,781	0.0120	0.0293	0.0000	0.0045	0.7093
EG_Index	17,781	1.0856	1.0551	0.0000	0.5000	4.5000
Size	17,781	22.5926	1.4480	17.3882	22.5846	30.6568
ROA	17,781	0.0071	0.0145	-0.2107	0.0059	0.2185
Growth	17,781	-0.1679	0.3732	-0.8997	-0.2166	1.6862

Table 2 shows the descriptive statistics of the core variables. The above statistics are obtained from the regression sample and the sample size used for descriptive analysis is identical to the regression sample. The average leverage ratio is 0.2010, while the median value is 0.1865, implying that the interest-bearing debt ratio of the sample firms is around 20%. The average value of lnAI is 0.0120, while the median is 0.0045; the levels of AI investment of firms included in this sample are quite low. However, there are considerable variations in the level of AI investment among the firms. The average value of EG_Index is 1.0856, while the median value is 0.5000; there are considerable variations in the performance of environmental disclosure. All continuous variables have been truncated at the 1% and 99% level. The above table shows descriptive statistics of the regression sample (N = 17,781).

4.2. Benchmark Regression Results

Table 3. Benchmark Regression Table

Variable	(1) Leverage	(2) Leverage	(3) Leverage
lnAI	0.2490 (0.0902)	-0.0125 (0.0733)	0.2010 (0.0961)
Size		0.0244*** (0.0020)	0.0327*** (0.0036)
ROA		-1.6998*** (0.0991)	-1.4483*** (0.1078)
Growth		0.0001*** (0.0000)	0.0001*** (0.0000)
Top1			-0.0005** (0.0002)
Dual			-0.0073** (0.0034)
CFO			0.0627*** (0.0145)
InstInvestor			-0.0004*** (0.0001)
Year FE	Control	Control	Control
Firm FE	Not control	Not control	Control
N	19,954	18,838	17,781
R^2	0.0190	0.0770	0.0910

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Same as above

Table 3 presents the benchmark regression results of AI investment on firms' interest-bearing debt ratios.Column (1): In column (1), when we take into account only the year dummy variable, the coefficient of lnAI is 0.2490; Column (2): In column (2), when we add the control variables to the model, the coefficient of lnAI is -0.0125; Column (3): In column (3), when we add the firm dummy variables to the model, the coefficient of lnAI is 0.2010, which is significant at the 5% level.

4.3. Mechanism Testing

Table 4. Mechanism Testing

Variable	(1) EG_Index	(2) Leverage
lnAI	-0.5507* (0.3281)	0.1998** (0.0957)
EG_Index		-0.0040*** (0.0013)
Size	0.1668*** (0.0146)	0.0334*** (0.0037)
ROA	1.0716*** (0.3443)	-1.4437*** (0.1075)
Growth	-0.0003 (0.0002)	0.0001*** (0.0000)
Top1	0.0039*** (0.0008)	-0.0004** (0.0002)
Dual	0.4830*** (0.0157)	-0.0053 (0.0034)
CFO	0.0090 (0.0269)	0.0628*** (0.0145)
InstInvestor	0.0014** (0.0006)	-0.0004*** (0.0001)
Year FE	Control	Control
Firm FE	Control	Control
N	32,307	17,781
R^2	0.2600	0.0920

The firms with high levels of AI score have low levels of environmental disclosure performance as AI investment might replace the allocation of resources to environmental governance (EG); the firms with good environmental disclosure performance have low interest-bearing debt ratios. The findings from the gradual regression indicate preliminary support for the resource trade-off approach and provide insights into the appropriateness of this trade-off. Table 4 presents the outcomes of the mechanism tests. As presented in Column (1), the coefficient of lnAI in relation to EG_Index is -0.5507 (p = 0.093); while in Column (2), the coefficient of EG_Index on Leverage is -0.0040 (p = 0.002). There is evidence of negative but marginally significant correlation between AI investment and environmental disclosure performance; there is also evidence of negative correlation between environmental disclosure performance and the interest-bearing debt ratio, thereby implying the resource trade-off process. The 95% Confidence Interval from the Bootstrap indirect effect test contains 0, thereby meaning that the indirect effect was not statistically significant.

4.4. Heterogeneity Analysis

Table 5. Heterogeneity Test Based on Firm Size

Variable	(1) Large Enterprise Division	(2) Small Enterprise Division
lnAI	0.3172** (0.1415)	0.1029 (0.0903)
Size	0.0221*** (0.0062)	0.0519*** (0.0072)
ROA	-1.4692*** (0.1246)	-1.2337*** (0.1789)
Growth	0.0000 (0.0000)	-0.0001 (0.0006)
Year FE	Control	Control
Firm FE	Control	Control
N	12,574	6,264
R^2	0.0566	0.1466

The results of the heterogeneity analysis based on the company size are presented in Table 5. Column (1) represents the group of large firms with an AI coefficient of 0.3172 that is significant at 5%; Column (2) represents the group of small firms with an AI coefficient of 0.1029 that is insignificant in terms of the significance test. Thus, the analysis based on the grouping regression shows that the AI coefficient is positively and significantly associated with the large enterprise group while not being significantly associated with the small enterprise group. This means that the positive correlation between AI and credit availability is more noticeable for large enterprises. For small enterprises, the coefficient is not statistically significant. Reasons for that might be that large enterprises have advanced information systems and greater opportunities to use AI technology, whereas, in small enterprises, there are still no benefits from the implementation of AI technology due to their technical constraints.

4.5. Robustness Tests

4.5.1. One-Period Lagged AI and PSM

Table 6. Robustness Test of One-Period Lagged AI and PSM

Variable	(1) Main Regression	(2) AI with a one-period lag	(3) PSM
lnAI	0.2010** (0.0961)		
L1_lnAI		0.2568*** (0.0997)	
lnAI (PSM)			0.2011** (0.0959)
Size	0.0327*** (0.0036)	0.0346*** (0.0036)	0.0328*** (0.0036)
ROA	-1.4483*** (0.1078)	-1.4817*** (0.1095)	-1.4605*** (0.1082)
Growth	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0001*** (0.0000)
Top1	-0.0005** (0.0002)	-0.0004** (0.0002)	-0.0005** (0.0002)
Dual	-0.0073** (0.0034)	-0.0082** (0.0034)	-0.0072** (0.0034)
CFO	0.0627*** (0.0145)	0.0622*** (0.0136)	0.0759*** (0.0129)
InstInvestor	-0.0004*** (0.0001)	-0.0004*** (0.0001)	-0.0004*** (0.0001)
Year FE	Control	Control	Control
Firm FE	Control	Control	Control
N	17,781	17,668	17,779
R^2	0.0910	0.0970	0.0920

In order to avoid selection biases, this paper uses the Propensity Score Matching (PSM) approach. The treatment dummy variable is "investment in AI" (AI_dummy), and the covariates are Size, ROA, Growth, Top1, Dual, CFO, and InstInvestor. The one-to-three nearest neighbor matching technique was used with a caliper equal to 0.05. Standardized differences of all covariates became less than 5% after matching, and there was no significant difference in all covariates between treatment and control groups. Thus, the balance condition is satisfied. The baseline model is re-estimated based on matched samples. The result is shown in Table 6, column (3). The coefficient of lnAI was 0.2011, and it was significant at 5%. It was the same as the result of the main regression. In this way, the baseline finding is robust. Columns (2) and (3) of Table 6 indicate that the coefficient of one-period lagged AI and the coefficient of lnAI after PSM matching were significantly positive. As can be seen from Table 7, the findings are robust with respect to substitution of AI_raw. The placebo test was passed.

4.5.2. Robustness Test of the AI Measure

Table 7. Robustness Test of the AI Measure

Variable	(1) Main Regression	(2) AI with a one-period lag	(3) PSM
lnAI	0.1727**	0.2338***	0.1728**
	(0.0847)	(0.0826)	(0.0845)
Size	0.0327***	0.0346***	0.0328***
	(0.0036)	(0.0036)	(0.0036)
ROA	-1.4489***	-1.4817***	-1.4611***
	(0.1078)	(0.1095)	(0.1082)
Growth	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)
Top1	-0.0005**	-0.0004**	-0.0005**
	(0.0002)	(0.0002)	(0.0002)
Dual	-0.0073**	-0.0082**	-0.0072**
	(0.0034)	(0.0034)	(0.0034)
CFO	0.0627***	0.0622***	0.0759***
	(0.0145)	(0.0136)	(0.0129)
InstInvestor	-0.0004***	-0.0004***	-0.0004***
	(0.0001)	(0.0001)	(0.0001)
Year FE	Control	Control	Control
Firm FE	Control	Control	Control
N	17,781	17,668	17,779
R^2	0.0910	0.0970	0.0920

These values are the robust standard errors. The raw level of AI investment (AI_raw) is in 100 million yuan units and has been winsorized at 1% and 99%. Column (1) contains the baseline regression results using AI_raw instead of lnAI; Column (2) contains the results of the regression with one-period lagged AI_raw; and Column (3) contains the results of the regression with PSM-matched sample. All the coefficients of AI are significantly positive, meaning that the core conclusion is robust and does not depend on the particular AI measurement method used.

After replacement of the lnAI variable by the raw level of AI investment (AI_raw), the coefficient of AI_raw in the baseline regression in Column (1) is 0.1727 ($p < 0.05$), and the coefficient of one-period lagged AI_raw in Column (2) is 0.2338 ($p < 0.01$); in Column (3), the coefficient of AI_raw in the PSM-matched sample is 0.1728 ($p < 0.05$). The results in all three columns are significantly positive, corresponding to the positive direction of the lnAI coefficient in the baseline regression, meaning that the core conclusion is robust and does not depend on the particular AI measurement method used.

4.6. Placebo Test

Table 8. Results of the Placebo Test

Metric	Value	Meaning
True beta	0.2010	The Effect of True AI on Leverage
500 random resampling runs	The true beta lies at the far right of the distribution	None of the pseudo-AI coefficients reached the true value
p-value (lower)	1.0000	All pseudo-AI coefficients were less than the true value
p-value (upper)	0.0000	The true beta is greater than all pseudo-AI coefficients

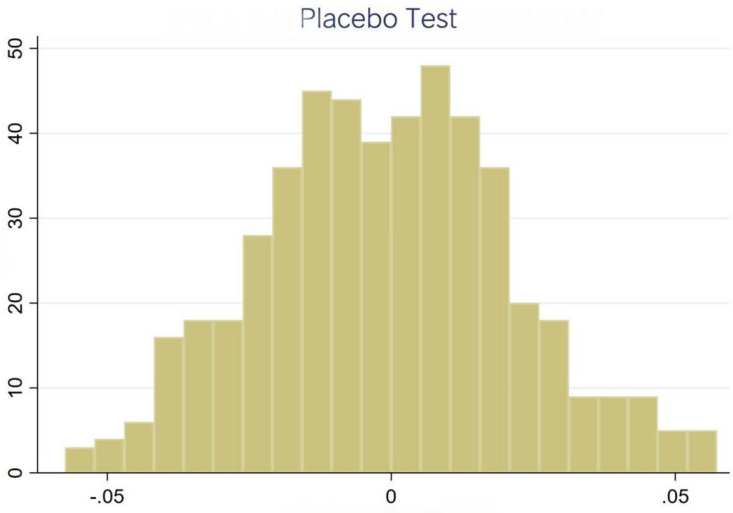


Figure 1. Placebo Test Plot

As shown in Table 8, the true coefficient (0.2010) lies at the far right of the distribution of 500 pseudo-AI coefficients, and none of the pseudo-AI coefficients reaches the true value. In order to see whether the baseline findings are based on random reasons, this study uses the placebo test. In particular, while keeping all control variables and the firm-year fixed effects in the baseline model unchanged, the level of AI investment is randomly permuted 500 times at the firm-year level. Then for each permutation, the baseline regression model is re-run, and the pseudo-AI coefficient is noted down. The true coefficient is the value of lnAI coefficient in the baseline regression, 0.201. The p-value is defined as the share of 500 permutations where the pseudo-AI coefficient is larger than or equal to the true coefficient. The findings reveal that in all 500 random permutations, the pseudo-AI coefficient is unable to achieve the value of the true coefficient ($p < 0.002$), demonstrating that the baseline findings are not influenced by random reasons.

Bootstrapping Results: Indirect effect: 0.0022, $p = 0.257$, the confidence interval contains 0. From bootstrapping re-sampling, the indirect effect is not significant, implying that the mediation effect of environmental disclosure performance failed the test of strict statistics.

5. Conclusion

Using the data of A-share listed companies in China between 2010 and 2023, the research analyzes the effect of the level of AI investment on a firm's interest-bearing debt ratio, and the role of the firm's environmental disclosure performance as an intermediary variable. The key results of the research are presented below.

Firstly, there is a statistically significant positive correlation between the level of AI investment and the interest-bearing debt ratio of a firm. Controlling for firm size, profitability, growth, capital structure, governance attributes, cash flow, and institutional ownership, the coefficient of lnAI is equal to 0.2010 and is statistically significant at the 5% significance level.

Secondly, mechanism tests show that AI investment has a negative relationship with environmental disclosure performance, and environmental disclosure performance has a negative relationship with the interest-bearing debt ratio. Insignificant results of the Bootstrap test suggest the lack of any evidence of resource trade-offs. The results of the stepwise regression test are compatible with the reasoning that AI investment draws away management resources from environmental disclosure performance, which can be considered as the short-term resource trade-off between corporate investment in AI technology and management of environmental disclosure performance. Investment in AI technology demands a great amount of resources, both financial and human, which might be squeezed out of management of environmental disclosure performance in the short term, while companies having high levels of environmental disclosure performance usually have enough cash flow and do not depend much on external debt.

Thirdly, heterogeneity tests show that the positive impact of AI investment on credit accessibility is observed among large-scale companies only. Large-scale companies have better information systems and a higher ability to apply AI technology; thus, they benefit from higher transparency and governance because of using AI. This impact is insignificant for small-scale companies.

Fourth, the robustness tests reveal that the baseline findings have a certain level of robustness. By implementing the robustness testing procedure, such as using the level of AI investment one period ago, performing Propensity Score Matching (PSM) analysis, and replacing raw values of AI, the coefficients of the explanatory variables are still positive and significant. Placebo tests also reveal that after randomly permuting the variable of AI, the coefficients of the pseudo-AI did not reach the actual values of the estimate, implying that the baseline findings are not generated by luck. Bootstrapping indirect effects test fails the significance test, which suggests no mediating role of environmental information disclosure performance.

First, from a theoretical perspective, this study identifies a positive relationship between the level of AI investments and interest-bearing debt financing by firms, which gives new empirical support for understanding the economic implications of AI investments of firms. Second, the relationship between AI investment and environmental disclosure performance is found to be negative; however, the Bootstrap indirect effect test fails to show significance, which implies that there is insufficient evidence regarding the mediation of environmental disclosure performance and should not be considered as a complete chain transmission mechanism. Third, from a practical perspective, heterogeneity analysis shows that the positive relationship between AI investment and interest-bearing debt financing is more pronounced in large firms, while small and medium firms might need to pay attention to their financing strategies when making AI investments.[17, 26, 32, 35]

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