AUTHOR STATEMENT

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The contributions of author are as follows:

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Conceptualization; Validation; Investigation; Methodology; Software; Resources; Visualization; Formal analysis; Data Curation; Writing - Original Draft; Writing - Review & Editing; Project administration

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The Dark Side of Artificial Intelligence on Information Quality: Evidence from Accounting Conservatism

Junze Li[1*] Wenqiu Zhang[2]

Abstract: Using data from Chinese A-share listed firms from 2012 to 2024, this study examines the impact of artificial intelligence on corporate accounting conservatism and its mechanisms. Employing the artificial intelligence innovation application pilot policy as a quasi-natural experiment, we construct a staggered difference-in-differences model. The results show that AI adoption significantly could reduce corporate accounting conservatism and it remains robust after multiple endogeneity tests such as instrumental variable approach. Mechanism tests indicate that enhanced management forecast ability and increased managerial myopia mediate the relationship between AI and accounting conservatism. Heterogeneity analysis reveals that predictive AI exerts a stronger negative effect on accounting conservatism than non-predictive AI. The main effect is more pronounced when bad news accumulation is low or when management faces greater performance pressure. This paper provides the first evidence of the adverse effect of AI from the perspective of accounting information quality and new insights for research on artificial intelligence and information disclosure while suggesting policy implications for capital market regulation.

Keywords: Artificial Intelligence; Accounting Conservatism; Management Myopia; Accounting Information Quality

JEL Classification: O33; M41; G32

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I. INTRODUCTION

Referring to prior studies (Basu, 1997; Zhong and Li, 2017), accounting conservatism should be regarded as a tendency to require a higher degree of verification for recognizing good news compared with bad news in financial statements. Therefore, earnings reflect bad news more sensibly than good news under prudence principles. Although the conceptual framework for financial reporting issued by FASB in 2024 has already excluded prudence or conservatism as an aspect of faithful representation because of its inconsistency with neutrality, it's still an important principle of accounting information quality which is influential to stakeholders and capital market effectiveness. For the creditors, accounting conservatism enhances the efficiency of debt contracts by timely loss recognition and requiring highly verifiable gains (Watts, 2003). For shareholders, conservatism helps mitigate agency problems through timely loss recognition (Ball and Shivakumar, 2005). Therefore, it remains necessary to explore new influencing factors of accounting conservatism and their governance implications, especially in the era of rapid digital technology development.

The development of artificial intelligence has facilitated information supply and demand in capital markets while also introducing challenges (Cao et al., 2023). Prior studies find that AI improves firms' disclosure quality (Li, 2026; Yang et al., 2025; Bertomeu et al., 2021) and enhances information interpretation and stock price informativeness in capital markets (Cheng et al., 2025; Bertomeu et al., 2025), and thus could reduce information asymmetry. However, no research has yet examined its specific impact on accounting information quality attributes, particularly accounting conservatism. Although AI optimizes governance processes and managerial decision-making (Brynjolfsson et al., 2016; Liu et al., 2025), its effect on accounting conservatism is not necessarily positive. Admittedly, AI could exert effective governance through strengthened internal and external monitoring (Fedyk et al., 2022; Zhang et al., 2025), nevertheless its black-box logic, algorithmic bias (Chen, 2024), and potential distortion of managerial behavior and cognition may generate adverse consequences. For instance, misleading information produced by AI could harm social welfare (Acemoglu, 2025). Therefore, what specific impact does AI adoption have on accounting conservatism, and through which channels does it operate?

To address the above question, we select the China's National Artificial Intelligence Innovation and Application Pilot Zones policy as the research setting. Due to the policy's characteristic of being implemented in batches across different regions over consecutive years, we construct a staggered difference-in-differences model to identify and analyze the impact of AI on accounting conservatism. Using data from Chinese A-share listed firms from 2012 to 2024, we find that the artificial intelligence adoption significantly reduces corporate accounting conservatism, and it remains robust after several tests including instrumental variables and placebo tests. Mechanism tests show that AI impairs accounting conservatism by enhancing firms' predictive capabilities and exacerbating managerial myopia, with both playing a partial mediating role. Heterogeneity analyses reveal that predictive AI exerts a more pronounced negative effect on accounting conservatism compared to non-predictive AI. Finally, the impairment of artificial intelligence on accounting conservatism is stronger when firms have less accumulated prior risk or when managers face greater short-term performance pressure.

This paper has three potential contributions. This paper is the first to examine the negative effects of artificial intelligence on accounting information quality, particularly on accounting conservatism. It offers a novel perspective on the effect of artificial intelligence in capital market information efficiency and provides supplementary evidence for research on AI and information disclosure. While prior studies have investigated AI's impact on corporate disclosure quality, including annual report quality (Li, 2026) and accounting information quality (Yang et al., 2025; Li et al., 2026), no literature has yet explored its effect on accounting conservatism, which is significant for information transmission and pricing efficiency in capital markets.

This paper further examines two channels through which artificial intelligence affects accounting information quality, including corporate predictive capability and managerial myopia, and thus clarifies the specific ,especially negative, mechanisms of AI in corporate data processing and disclosure. It also conducts heterogeneity analyses from perspectives such as AI's predictive capability to further probe the underlying reasons for its adverse effects. While prior research has analyzed mechanisms via internal control (Li, 2026) and external monitoring (Zhao et al., 2025), those studies primarily highlight positive impacts on

disclosure quality, overlooking potential negative effects and their mechanisms, particularly AI's distinctive economic property of superior predictive ability. Through mechanism and heterogeneity analyses, the manuscript enriches the literature on artificial intelligence and information quality and provides additional supporting evidence.

Finally, this study offers policy implications for governments and capital market regulators. By revealing the adverse effects of artificial intelligence on information disclosure, it supports stronger guidance and regulation of AI in corporate governance. It also assists firms in improving internal control systems, mitigating information asymmetry in capital markets, and enhancing pricing efficiency.

The rest of this paper is organized as follows. Section 2 discusses the relevant literature and develops the hypotheses. Section 3 describes the methodology and data. Section 4 reports and discusses the main results and robustness. Section 5 presents the mechanism test. Section 6 introduces the results of heterogeneity factors and Section 7 concludes.

II. HYPOTHESIS DEVELOPMENT

Traditionally, artificial intelligence is defined as the ability of intelligent agents to understand data, learn from it, and use that knowledge to achieve specific goals and tasks (Russell and Norvig, 2021). In an economic sense, existing research highlights that the core of artificial intelligence lies in its prediction capability, namely the dramatically reduced cost of using data to forecast unknown outcomes (Agrawal et al., 2018). Benefiting from its extensive information processing and predictive power, artificial intelligence not only profoundly shapes how capital markets understand and react to information (Bertomeu et al., 2025; Zhang et al., 2025), but also influences the quality of firms' information supply. According to prior studies, AI adoption significantly improves the readability and accuracy of listed companies' annual reports (Li, 2026). Meanwhile, AI helps reduce the degree of earnings management (Li et al., 2026) and improves the quality of information disclosure (Yang et al., 2025). However, the specific impact of artificial intelligence on the quality of accounting information remains to be further explored, and the relationship may be complex. The output of accounting information stems from corporate management processes and managerial decision-making, while the effects of AI on processes and decisions could be

multidimensional, and thus produces unpredictable impacts on accounting information quality, particularly the conservatism. Notably, due to the black-box nature of AI algorithms, whether their impact on accounting conservatism is invariably positive is open to doubt. We examine the potential effects of AI on accounting conservatism from two opposing perspectives.

On the one hand, AI adoption may help improve accounting conservatism. First of all, AI could enhance corporate data management capabilities and the accuracy of information governance. AI ensures proper implementation of complex accounting standards such as FAS 133 (Le Guyader, 2020). Machine learning improves the accuracy of managerial accounting estimates and mitigates the impact of objective estimation biases on accounting information quality, then reduces the likelihood of material accounting errors (Ding et al., 2020; Bertomeu et al., 2021). Artificial intelligence could also increase the efficiency and accuracy of routine data processing in corporate data management, so that it decreases human errors (Liu et al., 2025). For instance, machine learning models predict warranty reserves more accurately than human experts, particularly by avoiding aggregation bias and anchoring to historical costs present in human estimation models (Becker and Schölzel, 2025). Because of the improved information governance efficiency, firms could process earnings-related data more effectively, enabling timelier recognition of bad news in capital markets and thus enhancing accounting conservatism.

Secondly, artificial intelligence could strengthen internal controls and audit oversight. Prior studies have shown that machine learning enables effective monitoring of management activities (Bao et al., 2020; Bertomeu et al., 2021). In management practices, AI adoption significantly improves corporate internal controls (Monteiro et al., 2023), and then enhance firms' financial transparency (Zhao et al., 2025). In financial firms, AI application strengthens internal controls and management, leading to improved financial performance (Cheng et al., 2025). Moreover, AI bolsters external audit supervision (Samiolo et al., 2024). In recent years, the adoption rate of AI in audit work has steadily increased (Kokina et al., 2025). AI helps maintain auditors' perceived objectivity and significantly reduces the adverse impact of independence conflicts on audit quality (Libby et al., 2024). The use of AI in auditing reduces material restatements related to contingent items and revenue recognition (Fedyk et al., 2022) and shortens the annual audit report cycle, thereby improving the timeliness of audit reports

(Liao et al., 2024). Enhanced internal and external monitoring pressure compels management to adhere more strictly to compliance requirements and accounting conservatism principles in information disclosure. At the same time, bad news from capital markets further intensifies internal and external regulatory scrutiny (Ashbaugh-Skaife et al., 2009), especially after 2013 when Chinese stock exchanges started to implement the inquiry letter system, which also attracts regulatory attention to the adverse information. Consequently, as AI advances, listed companies may be compelled to increase their accounting conservatism.

On the other hand, AI adoption may also reduce accounting conservatism. Firstly, AI objectively enhances firms' predictive capabilities. The previous studies have found that AI effectively mitigates uncertainty interference in complex environments and further extends cross-domain technological forecasting ability (Qu et al., 2026). Philipp et al. (2024) and Doshi et al. (2024) show that ensembles of multiple large language models are able to match the predictive accuracy of human crowds and effectively incorporate additional human provided information to calibrate predictions. By improving firms' information acquisition and processing on the demand side, AI strengthens their ability to forecast market dynamics (Paschen et al., 2019). Firms will leverage machine learning to enhance accounting estimates, fraud detection and prediction of misstatements (Jones and Free, 2026). Finally, artificial intelligence boosts corporate risk identification and forecasting capabilities (Chen et al., 2026). As AI empowers stronger predictive ability, managers' perception of future uncertainty significantly declines. Under the conservatism principle, when future outcomes cannot be accurately anticipated, firms should recognize losses promptly and defer revenue recognition. Therefore, AI causes management to relax prudent stances by improving firms' predictive power, and thus impairs accounting conservatism. Furthermore, powerful predictive capabilities could also exacerbate managerial overconfidence, which may lead to more aggressive accounting estimates and policies, which will further reduce accounting conservatism as well.

Additionally, AI may increase managerial myopia and then reduce corporate accounting conservatism. Artificial intelligence systems increase the quantifiability of firms' short-term performance (Zhang et al., 2023). Through real-time data capture and analysis, AI converts previously hard-to-quantify metrics, including market performance, customer feedback, and

operational efficiency, into visualized short-term performance indicators. Existing literature shows that firms will use AI to more accurately assess performance and design personalized incentive plans (Varma et al., 2024). The real-time performance feedback induced by AI will strengthen dynamic evaluation of short-term performance (Buck et al., 2018). Consequently, managerial attention inevitably shifts toward quantifiable short-term objectives, leading to a preference for choices that favor current-period performance and avoid fluctuations in short-term metrics. Meanwhile, the effects of traditional management decisions often take considerable time to materialize, whereas AI enables rapid tracking and analysis of decision outcomes, quickly translating them into measurable outputs (Brynjolfsson et al., 2016; Chen et al., 2012). As a result, immediate adjustments to accounting policies and estimates provide stronger positive incentives for short-term earnings, motivating firms to prioritize short-term performance. In addition, AI's enhanced identification of bad news in capital markets and its consequences may reduce firms' sensitivity to market dynamics, further exerting a negative impact on accounting conservatism.

In summary, the application of artificial intelligence in accounting exhibits a pronounced double-edged sword effect. Admittedly, AI supports accounting conservatism by optimizing data governance, strengthening internal controls and audit oversight, so that it will enhance the reliability of accounting information and the timely recognition of bad news. Nevertheless, AI markedly improves prediction accuracy, reduces perceived uncertainty, and exacerbates managerial myopia through real-time performance quantification, which may undermine the conservatism of accounting information.

Based on the above analysis, we propose the following competitive hypotheses:

H1a: Corporate AI adoption could enhance accounting conservatism.

H1b: Corporate AI adoption could impair accounting conservatism.

III. VARIABLE DEFINITION & RESEARCH DESIGN

Accounting Conservatism

According to the definition formerly issued by the Financial Accounting Standards Board (FASB) in 1980, accounting conservatism is described as a prudent reaction to uncertainty to try to ensure that uncertainties and risks inherent in business situations are

adequately considered. Thus, if two estimates of amounts to be received or paid in the future are about equally likely, conservatism dictates using the less optimistic estimate. And it's much as known as the definition of prudence, which is defined in conceptual framework of International Accounting Standard Board, is the exercise of caution when making judgements under conditions of uncertainty. It requires that the exercise of prudence means that assets and income are not overstated and liabilities and expenses are not understated.

Following prior research (Vishal, 2022), the timeliness of earnings in responding to bad news in capital markets reflects accounting conservatism in recognition and measurement. Therefore, we employ the Basu model to measure firm-level accounting conservatism (Basu, 1997; Lara et al., 2016). Specifically, the estimated coefficient on the interaction term between stock returns and the loss dummy serves as the proxy for accounting conservatism (Basu). This indicator captures the incremental sensitivity of earnings to "bad news" relative to "good news"; a larger value indicates stronger conservatism.

AI Innovation and Application Pilot Zones

To further promote the innovative development and application of artificial intelligence, the seventh meeting of the Central Commission for Deepening Overall Reform, held in March 2019, adopted the Guiding Opinions on Promoting the Deep Integration of Artificial Intelligence and the Real Economy, establishing the top-level design for empowering the real economy with AI. Pursuant to this policy, the Ministry of Industry and Information Technology successively approved the establishment of four batches of National Artificial Intelligence Innovation Application Pilot Zones, which covers 11 cities, municipalities, and districts or counties. Appendix A reports the establishment and locations of all pilot areas.

Referring to the previous studies (Li, 2026; Liu et al., 2025), we construct the explanatory variable based on a staggered DID model. The Artificial Intelligence Innovation Application Pilot Zone indicator (AIIAPZ) is formed by the interaction term of Treat and Post. Specifically, Treat is a dummy variable distinguishing treatment and control groups. It equals 1 if firm i's headquarters is located in a pilot region, and 0 otherwise. Post is a dummy variable capturing the policy shock year, which is equal to 1 in the year t and thereafter when firm i's region is designated as a pilot zone, and 0 otherwise. Consistent with existing research (Lin et al., 2025), pilot zones implemented in the first half of the year are treated as

starting in that year, while those implemented in the second half are treated as starting in the following year. Due to the inclusion of time fixed effects and firm fixed effects, which induce multicollinearity with Treat and Post, only the interaction term AIIAPZ is included in the regression model.

Control Variables

According to prior studies (Vishal, 2022; Fu et al., 2025), we select control variables that may affect accounting conservatism from the dimensions of firm financial characteristics and internal/external governance characteristics.

Financial characteristic control variables include firm size (Size), capital structure (Lev), profitability (ROA), growth ability (Growth), and market performance (BM). Internal governance variables include separation of ownership and control (Separation), CEO-chair duality (Dual), proportion of independent directors (Indep), board size (Board), ownership concentration (Top1), and ownership checks and balances (Balance). External governance variables include Big 4 auditors (Big) and audit opinion type (Audit). Appendix B reports the detailed definitions and sources of all the above variables.

Data and Sample

This paper uses all listed firms on the Shanghai and Shenzhen Stock Exchanges from 2012 to 2024 as the initial sample, and excludes those with special treatment designations (ST/*ST). Financial firms, whose CSRC industry code begins with J, are then excluded. Further, observations with missing key variables or extreme values are dropped. The final sample comprises 37,360 firm-year observations from 4,889 firms.

Firm governance data were obtained from the CSMAR database. The accounting conservatism measure was constructed based on these data using the Basu model. Artificial intelligence patent data were sourced from the China National Intellectual Property Administration database and manually processed. Regional-level data were drawn from the China City Statistical Yearbook and the China Statistical Yearbook. Other financial data were obtained from the Wind database.

Descriptive Statistics and Univariate Analysis

Panel A of Table 1 reports the descriptive statistics. The dependent variable Basu has a mean value of 1.3312 and a median of 0.0849. The mean exceeds the median, so that it

implies a right-skewed distribution overall, such that most Chinese listed firms still maintain a basic level of accounting conservatism. The standard deviation of Basu is 5.0313, which reflects a substantial variation in accounting conservatism across firms and years. The mean of AIIAPZ is approximately 0.2301, meaning about 23% of firm-years in the sample are affected by the policy, consistent with prior studies (Li, 2026; Liu et al., 2025). The distributions of the remaining control variables also align with those reported in earlier research.

Furthermore,according to previous studies (Cheng et al., 2025), we employ Python to the number of AI keywords in the MD&A sections of annual reports. The natural logarithm of this count was then used as the measurement of the AI adoption level in each year. We split the sample using the year-city level median; otherwise, univariate analysis would fail to capture the policy's time-trend effects. Panel B of Table 1 reports the univariate analysis results. The mean value of Basu for the treatment group is approximately 2.139, substantially higher than 0.872 for the control group, with the difference significant at the 1% level. This suggests that AI adoption may lead to relatively lower accounting conservatism, providing preliminary support for H1b and rejecting H1a. We also conduct correlation analysis on the main variables. Appendix C reports the Pearson matrix. Correlation coefficients among main variables are all below 0.5, and VIF values are all below 3, ruling out multicollinearity concerns. Interestingly, the correlation between AIIAPZ and Basu is 0.018 and positive at the 1% level, which may indicate omitted-variable bias in the single variable analysis. In the subsequent multivariate regressions, we further examine their relationship while addressing potential endogeneity.

[Insert Table 1 about here]

IV. EMPIRICAL RESULTS & ANALYSIS

Baseline Regression Model

As shown in model (1), we construct a staggered DID model with high-dimensional fixed effects to examine the impact of artificial intelligence on corporate accounting conservatism. $Accounting_Conservatism_{i,t}$ represents the accounting conservatism of

firm i in year t. $AIIAPZ_{i,c,t}$ is the independent variable indicating the AIIAPZ pilot status of city c in year t. $Controls_{i,t}$ is a vector that contains all the control variables, though We gradually add different categories of control variables into the regression model. We employ the coefficient α_i, λ_t and ξ_c to respectively indicate the firm, year and city level fixed effects and report t value based on standard errors clustered at the industry level. We mainly focus on the estimated coefficient β_1 and its t-value.

$$Accounting_Conservatism_{i,t} = \alpha_i + \lambda_t + \xi_c + \beta_0 + \beta_1 AIIAPZ_{i,c,t} + \beta_2 Controls_{i,t} + \varepsilon_{i,t} \quad (1)$$

Artificial Intelligence and Corporate Accounting Conservatism

Table 2 reports the impact of AIIAPZ on corporate accounting conservatism. Column (1) includes no control variables. Columns (2) and (3) progressively add firm financial characteristics and internal governance variables. Column (4) includes all control variables. As shown in Table 2, after controlling for all variables and fixed effects, the estimated coefficient on AIIAPZ remains significantly negative at the 5% level across specifications, indicating that AI innovation and adoption significantly reduce firm accounting conservatism. The above findings support H1b and rejects H1a. According to prior research (Correia, 2015), the minor sample attrition results from the high-dimensional fixed effects model dropping singletons, and the slight proportion won't affect overall sample representativeness or result robustness. Economically, in column (4), a one-standard-deviation increase in AI adoption decreases accounting conservatism by approximately 7.44% of a standard deviation.

[Insert Table 2 about here]

Referring to prior literature (Baker et al., 2010), we conduct a parallel trend test by plotting the time trends. Specifically, we generate interaction terms between year dummies and the treatment group dummy, then include them as explanatory variables in the regression model. As shown in Figure 1, the confidence intervals of the estimated coefficients include zero before the policy intervention, which indicates that there were no significant differences between the treatment and control groups before the establishment of the AIIAPZ. The above results show that the overlapping DID model based on high-dimensional fixed effects passes the common trend test.

[Insert Figure 1 about here]

Heterogeneous Robust DID Estimator

In staggered DID models, the weighted average of treatment effects can have negative weights, causing OLS estimates to deviate from, or even oppose the true effect (Baker et al., 2022; Athey and Imbens, 2022; de Chaisemartin et al., 2020). Therefore, referring to previous study (Callaway and Sant'Anna, 2021), we group treated units by their first treatment timing and estimate weighted average treatment effects.

Table 3 reports heterogeneous robust estimates of AI's impact on corporate accounting conservatism. In columns (1), (3) and (5), we report the simple weighted average treatment effects estimated using inverse-probability-weighted OLS, inverse-probability weighting, and OLS respectively. The ATT estimates are -0.7625, -0.7124 and -0.7468, all significant at the 1% level. This indicates that AIIAPZ designation, which typically signals higher firm-level AI adoption, substantially reduces accounting conservatism. In columns (2), (4), and (6), we present the dynamic ATT based on the same three methods. Pre-treatment average treatment effects are insignificant, whereas post-treatment estimates are negative and significant at the 1% level across specifications. These findings further confirm the adverse effect of AI on accounting conservatism and support the validity of the parallel trends assumption through the dynamic ATT patterns.

[Insert Table 3 about here]

Bacon Decomposition

Following previous study (Goodman-Bacon, 2021), we employ the Bacon decomposition method to analyze the composition of high-dimensional fixed effects estimators. Table 3 reports the results of bacon decomposition. It reveals that about 79.86% of the weight in the HDFE estimator is derived from the reliable "Never-treated vs. Timing" comparisons, which yield negative and significant coefficients. The negligible weights of other groups ensure that it won't materially distort the overall average treatment effect and then confirms the primary results are not driven by heterogeneous bias. Consequently, Bacon decomposition validates the robustness of ATT.

[Insert Table 4 about here]

Two-stage Least Squares Method

To address potential endogeneity concerns, we introduce an instrumental variable into the baseline regression model. Referring to prior studies (Feyrer et al., 2019;

Goldsmith-Pinkham et al., 2020), we construct the instrument as the interaction between baseline historical data and time trends. Specifically, we use the number of AI firms in each prefecture-level city in the year prior to policy implementation (2018) as a proxy for baseline regional AI development level (AIFirms2018). The initial data about AI firms are sourced from the China Industry and Commerce Enterprise Database. Firms are identified as AI-related based on whether their business scope includes AI-relevant keywords. Following prior studies (Feyrer et al., 2019; Goldsmith-Pinkham et al., 2020), we employ the annual number of internet broadband access ports per province as a time-trend control for AI development and adoption, compiled from the National Bureau of Statistics and China Telecommunications Industry Reports. The interaction between these two variables serves as the instrumental variable (IV). The validity of this IV rests on its strong correlation with AIIAPZ designation, driven by regional AI firm presence and internet infrastructure, while having no direct link to firm-level accounting information quality.

Table 5 presents the two-stage least squares regression results. In the first stage, the coefficient on IV for AIIAPZ is 0.9599 and significant at the 1% level, which indicates that regions with stronger pre-existing AI development are more likely to implement the AIIAPZ policy. In the second stage, the coefficient on AIIAPZ is -2.8387, negative and significant at the 5% level, so that it implies that AI adoption reduces corporate accounting conservatism and is consistent with baseline findings. The Cragg-Donald Wald F and KP Wald F statistics for the instrumental variable are 8831.26 and 494.64, which both exceed the 10% critical value, so that passing weak identification test (Cragg and Donald, 1993; Stock and Yogo, 2005). The p-value of the Kleibergen-Paap LM statistic is less than 0.01, which means that the 2SLS results pass the under-identification test.

[Insert Table 5 about here]

Placebo Test

Following prior studies (Cantoni et al., 2017; Li et al., 2016), we also conduct a placebo test by randomly assigning treatment and control groups to address endogeneity concerns. We randomly assign firms to either the treated group or the control group, and then re-estimate model (1) 1000 times. Figure 2 reports the kernel density and p-values of 1000 times regression estimate coefficients. The coefficients of AIIAPZ are mostly concentrated around

zero and presents an approximate normal distribution and most of the estimated p-values are greater than 0.1, which exempt the possibility of the estimation results being obtained by chance. Additionally, the estimated coefficient on the real treatment lies in the left tail of the placebo coefficient distribution and is far from the main mass of placebo estimates. The above distributions indicate a significant difference between the true treatment effect and randomly generated placebo effects, therefore the main results are not obtained by chance.

[Insert Figure 2 about here]

Entropy Balancing Method

In order to control the multidimensional balance of covariates between the treatment and the control group sub-samples, we employ entropy balancing method to address endogeneity concerns according to prior studies (Hainmueller, 2012; Hainmueller et al., 2013). First of all, we select all control variables as the initial group of covariates. Then We generate the interaction terms among all these covariates and their secondary and third moments, which are included as an extended group of covariates in the balancing procedure. Panel A of Table 6 presents the results of the balancing tests. After adjustment, the means and standard deviations of initial covariates in the control group are essentially identical to those in the treatment group.

Panel B of Table 6 reports high-dimensional fixed effects and heterogeneous robust estimates after entropy balancing matching. In columns (1) and (2), the coefficients on AIIAPZ are -0.8079 and -0.8052, both negative and significant at the 5% level. In columns (3) and (4), the simple weighted average treatment effect and dynamic average treatment effect estimated via inverse-probability OLS are -0.6694 and -0.7173, both negative and significant at the 1% level, with pre-treatment effects insignificant. These results continue to confirm the weakening effect of AI adoption on corporate accounting conservatism, supporting H1b and the robustness of baseline findings.

[Insert Table 6 about here]

Alternative Measurements of Variables

In addition to the above approaches, we also conduct supplementary tests by substituting variables. Referring to previous studies (Khan and Watts, 2009; Khalilov and Osma, 2020), we used the CScore model to measure corporate accounting conservatism and employed it as

the dependent variable. Table 7 reports the robustness check results of this variable substitution. Regardless of the estimation methods or calculation approaches for average treatment effects, the impact of AIIAPZ on corporate accounting conservatism remains consistently significant, and it also passes the parallel trend test.

[Insert Table 7 about here]

V. MECHANISM TESTS

Forward Information of Managerial Decision

The widespread application of artificial intelligence enhances firms' ability to acquire and analyze forward-looking information (Brynjolfsson et al., 2016), and thus influencing management's choices regarding short-term accounting estimates and policies. Theoretically, accounting conservatism stems from information asymmetry and future uncertainty. When managers lack sufficient information about future events, prudence dictates that losses should be recognized promptly while gains are deferred. However, artificial intelligence alters this premise. With big data and algorithms, firms could gain access to more information about expectations and market performance, which reduces management's perception of uncertainty about the future (Pu et al., 2025) and encourages the use of optimistic assumptions in accounting estimates. In this respect, by enhancing the ability to acquire forward-looking information, AI objectively weakens the prudence on which accounting conservatism is built.

According to prior research (Goodman et al., 2014; Hilary and Hsu, 2011), we use management forecast error to measure a firm's ability to acquire forward-looking information. Consistent with the approach of Baik et al. (2011), we first convert forecasted net income into earnings per share and then compare it with actual earnings per share. Management earnings forecasts generally include range forecasts and percentage forecasts. For range forecasts, we use the midpoint of the upper and lower bounds. For percentage forecasts, we take the midpoint of the upper and lower bounds and multiply it by the prior year's net income to obtain the forecasted value for the current year. If a firm provides a forecast in the form of a growth target, such as "not exceeding 30%," We multiply that target percentage by the prior year's net income to derive the forecast. Finally, if a firm uses "Net Profit attributable to Equity Holders of the Company" as the forecast target, we first convert it into forecasted

earnings per share attributable to shareholders of the parent company and then compare it with the actual earnings per share attributable to shareholders of the parent company reported in the annual report. We define the variable Pre_Bias as the absolute difference between forecasted and actual earnings per share. A larger value of Pre_Bias indicates a greater forecast error and lower accuracy, suggesting weaker management forecasting ability. Additionally, we compute the three-year rolling average of this forecast error (Pre_Bias_Mean) to more reliably measure management's forecasting ability over a specific period.

Panel A of Table 8 reports the results of the mediation analysis based on management forecasting ability. In columns (1) and (3), the coefficients of AIIAPZ on Pre_Bias and Pre_Bias_Mean are -0.0027 and -0.0031, respectively, and are significantly negative at the 5% and 1% levels. It indicates that the adoption of artificial intelligence reduces management forecast errors and enhances management forecasting ability. In columns (2) and (4), after controlling for these mediating variables, the effect of AIIAPZ on accounting conservatism remains significantly negative at the 5% level, suggesting that management forecasting ability serves as a partial mediator. The application of artificial intelligence improves firms' ability to acquire forward-looking information, and thus amplifies management's optimistic bias and ultimately exerting a negative impact on accounting conservatism. We further test the significance of the mediation effect. The Sobel Z-statistics are significant at the 1% level, confirming the presence of a mediation effect through management forecasting ability.

Time Preference of Managerial Decision

The adoption of AI may also subjectively exacerbate managerial myopia, and then impairs accounting conservatism. AI is characterized by its capacity for immediate feedback. After implementing AI systems, firms can monitor and present operational data, such as production, sales, and inventory in real time, allowing the outcomes of managerial decisions to be observed and evaluated promptly (Sharma et al., 2014; Brynjolfsson et al., 2016). To avoid negative assessments triggered by short-term performance fluctuations, management tends to favor accounting estimates and policies that enhance current-period financial statements (Paul et al., 1999). For instance, when facing indications of asset impairment, firms may choose to delay loss recognition. At the same time, they tend to adopt lower

estimates in provisioning to smooth earnings. In other words, AI intensifies management's sensitivity to short-term results, leading them to prioritize immediate gains and, over time, deviate from the principle of prudence in accounting practices.

Following prior studies (Sheng et al., 2022; Zhang et al., 2023; Bushee, 1998), we measure managerial myopia based on management's disclosure behavior and investment behavior. First, we use Python to segment the MD&A text in listed firms' annual reports and perform word frequency analysis based on an existing Chinese myopia dictionary (Hu et al., 2021; Sheng et al., 2022). We then compute the proportion of these keywords to the total number of words in the MD&A section as a measure of managerial myopia (Myopia_Dis). Second, we use the reduction in R&D expenditures to proxy for myopic managerial behavior (Myopia_Inv). This proxy is calculated as the difference in R&D expenditures between year t and t-1, scaled by total assets in year t-1. A smaller value indicates a higher degree of managerial myopia.

Panel B of Table 8 presents the results of the mechanism test from the perspective of managerial myopia. In columns (1) and (3), the coefficients of AIIAPZ on Myopia_Dis and Myopia_Inv are 0.0026 and -0.0010, respectively, with significance levels of 5% or higher. This indicates that AI adoption exacerbates managerial myopia. In columns (2) and (4), after controlling for these mediating variables, the coefficients of AIIAPZ on Basu are -0.8909 and -0.8907, respectively, both significantly negative at the 5% level. These results suggest that AI adoption reduces corporate accounting conservatism by intensifying managerial myopia, and imply that managerial myopia serves as a partial mediator. Finally, the Sobel Z-statistics are significant at the 5% level, confirming the existence of the mediation effect.

[Insert Table 8 about here]

VI. HETEROGENEITY ANALYSIS

Types of Artificial Intelligence

Existing studies categorize AI into different types. Decision intelligence is used to optimize strategies (Yablonsky, 2019), while automation-type AI enhances efficiency by reducing repetitive human labor (Acemoglu and Restrepo, 2018). Therefore, compared to AI with limited predictive capabilities, such as industrial robots as defined in previous studies,

AI with predictive capabilities may be more conducive to firms' forward-looking information acquisition and evaluation of market signals, thereby influencing accounting conservatism.

We classify AI-related patents into different categories based on whether the AI possesses predictive capabilities. Following existing research (Li, 2026), we first adopt the "Classification System for Key Digital Technology Patents (2023)" issued by the China National Intellectual Property Administration (CNIPA) as the criteria for identifying AI patents. In this framework, the authority categorizes AI-related patented technologies into three dimensions: AI hardware platforms, general AI technologies, and key AI technologies. These dimensions encompass 14 secondary technology branches and 27 tertiary technology branches, each associated with corresponding IPC classification codes. After legally scraping patent data for all listed firms from the CNIPA official database using Python, we screen all AI patents from 2012 to 2024 based on these IPC codes. Furthermore, according to prior study (Kelly et al., 2021), we employ text analysis to classify patents into detailed categories. Specifically, AI patents without predictive abilities are primarily designed for automation, with its patent abstracts containing keywords such as "automation", "unattended", or "RPA". And the abstract of AI patents with predictive abilities should as least include the key words such as "predict", "forecasting", "detection", "generate", "prompt" or "synthetic". If a patent's abstract contains keywords from multiple categories, it is assigned to all relevant types. We then aggregate the number of patents of each type for each firm-year, add one, and take the natural logarithm to construct the independent variables. Finally, we obtain the following two proxy variables: Non_PreAI (non-predictive AI patents) and PreAI (predictive AI patents).

Table 9 reports the heterogeneity analysis results for different types of AI. In columns (1) and (2), the estimated coefficients of Non_PreAI on Basu are not significant. In columns (3) and (4), the number of predictive AI patents exhibits a significantly negative coefficient with corporate accounting conservatism, which indicates that AI with predictive capabilities are more likely to lead to a decline in accounting conservatism compared to non-predictive AI. It corroborates the argument that AI reduces accounting conservatism by increasing managerial predictive ability.

[Insert Table 9 about here]

Bad News Backlog

Accounting conservatism is inherently characterized by the "timely recognition of bad news." When a firm has accumulated a substantial amount of bad news in prior periods, its accounting information is already at a relatively low level of conservatism, leaving limited room for further decline. At the same time, the accumulation of bad news itself constitutes a potential risk signal that constrains management's optimistic tendencies. Even if AI provides relatively optimistic forecasts about the future, management cannot entirely disregard these accumulated risks when making aggressive accounting estimates in the presence of existing negative factors. Moreover, from an external monitoring perspective, when a firm has a high level of accumulated bad news, auditors, regulators, and investors tend to pay greater attention, which curbs management's incentive to exploit AI's informational advantages for earnings manipulation. Therefore, under conditions of high bad news accumulation, the negative impact of AI on accounting conservatism is likely to be mitigated.

Following prior research (Zhang et al., 2025), we use stock price crash risk to measure the accumulation of bad news in prior periods. Stock price crash risk refers to the probability of a sudden and substantial decline in a listed firm's stock price, that is, the likelihood of extreme negative values in firm-specific stock returns, which reflects the extent of bad news accumulation. When firms disclose bad news in a timely manner, capital markets provide relatively prompt feedback on stock prices, resulting in lower crash risk, and vice versa. Therefore, higher crash risk indicates a greater accumulation of bad news in prior periods. Consistent with prior studies (Zhang et al., 2025; Kim et al., 2014), we employ two firm-specific crash risk measures, including the negative coefficient of skewness (NCSKEW) and down-to-up volatility (DUVOL). Both measures are based on weekly stock returns at the firm level and account for market-wide fluctuations and the impact of non-synchronous trading on individual stock returns. We compute these measures using weekly stock return data from the year prior to the annual report release and partition the sample based on their median values.

Table 10 reports the heterogeneity analysis results based on prior bad news accumulation. In columns (1) and (3), we examine the impact of AI on accounting conservatism under conditions of low NCSKEW and low DUVOL, respectively. The coefficients of AIIAPZ on Basu are -0.8949 and -0.8086, both significantly negative at the 1% level. However, when

prior bad news accumulation is high, when stock price crash risk is elevated, the coefficients of AIIAPZ on Basu are only significant at the 10% level, with magnitudes notably smaller than those in the sub-sample with low bad news accumulation. These findings suggest that when a firm has accumulated substantial bad news in prior periods, management lacks both the incentive and the latitude to further reduce accounting conservatism, even though AI provides informational support for decision-making. This also reflects a negative feedback mechanism from capital markets regarding declines in accounting conservatism.

[Insert Table 10 about here]

Performance Pressure

Finally, we conduct heterogeneity analysis from the perspective of short-term performance pressure. Performance pressure refers to the external pressure faced by management when there is a gap between actual firm performance and expected performance, typically shaped by analyst forecasts and shareholder expectations. When firms face strong short-term performance pressure, management becomes more focused on current-period profits. Under such circumstances, the shortened decision feedback cycle and increased visibility of short-term performance brought about by AI further exacerbate their myopic tendencies (Waller et al., 2013). On the other hand, when performance pressure is high, management also has stronger incentives to engage in earnings manipulation.

Referring to prior studies (Schulz and Wiersema, 2018; Zhong et al., 2026), we measure managerial performance pressure as the difference between analysts' forecasted net income and the firm's actual net income for the year, scaled by total assets at the end of the period. Analysts' forecasted net income is calculated as the average of all analyst forecasts for a given firm in a given year. A larger value of this measure indicates greater managerial performance pressure. Furthermore, since performance pressure in the current year arises only after a performance expectation gap in the prior year, we use the one-period lagged value of this indicator. In addition, we compute the rolling average of managerial performance pressure over the past two years as a proxy for cumulative performance pressure. Finally, we partition the sample based on the median value of these measures.

Table 11 reports the heterogeneity analysis results based on performance pressure. In columns (1) and (3), the coefficients of AIIAPZ are -0.4947 and -0.3586, respectively, with

only column (1) exhibiting a marginally significant negative effect at the 10% level. In columns (2) and (4), the estimated coefficients of AIIAPZ are -1.2751 and -1.1578, both significantly negative at the 5% level. These findings suggest that managerial performance pressure positively moderates the impact of artificial intelligence on accounting conservatism. When managers face greater performance pressure, they have stronger incentives to embellish accounting earnings, and AI objectively provides feasible support for their actions that reduce accounting conservatism. Conversely, when performance pressure is low, this effect is limited.

[Insert Table 11 about here]

VII. CONCLUSIONS

Artificial intelligence has profoundly influenced the dissemination of information in capital markets, affecting both information demanders (Bertomeu et al., 2025) and information suppliers (Li, 2026; Zhang et al., 2025). However, its role in corporate information disclosure may not always be beneficial. In fact, the widespread application of AI, coupled with insufficient regulatory oversight, may adversely affect information quality, thereby exacerbating information asymmetry and impairing the efficiency of price mechanisms in capital markets.

Using a quasi-natural experiment based on AI innovation application pilots and data from Chinese listed firms over the period 2012 to 2024, this paper empirically examines the impact of artificial intelligence on corporate accounting information quality, with a particular focus on accounting conservatism. The findings reveal that the adoption of AI significantly reduces corporate accounting conservatism, and this result remains robust across a variety of robustness tests. Mechanism analysis indicates that AI negatively affects accounting conservatism both by objectively enhancing firms' predictive capabilities and by subjectively exacerbating managerial short-termism. Furthermore, the effect of AI on accounting conservatism exhibits technological heterogeneity, with predictive AI demonstrating a stronger negative impact. Finally, the dampening effect of AI on accounting conservatism is more pronounced when firms have less accumulated bad news or face greater short-term

performance pressure.

We further propose several potentially feasible recommendations. First, in the context of rapid iterations in large AI models, governments should strengthen the regulation of large model applications, despite the fact that they have already required information disclosers to label and review content generated by AI. Meanwhile, capital market regulators should further enhance the supervision of information disclosure quality, maintaining fundamental market order through mechanisms such as inquiry letters and random inspections. In addition, firms should reinforce the management of AI applications and information quality at the managerial level, and mitigate the negative effects through approaches such as strengthening internal controls. Finally, appropriate incentive mechanisms and relief from performance pressure may help reduce management's motivation to embellish accounting information.

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Figure 1 Common Trend Test

Figure1 shows the β coefficient estimates and 95% confidence intervals from the following regression model mentioned below, where i indicates firms and t indicates year. The β coefficients captures average treatment effect (ATT) estimates.

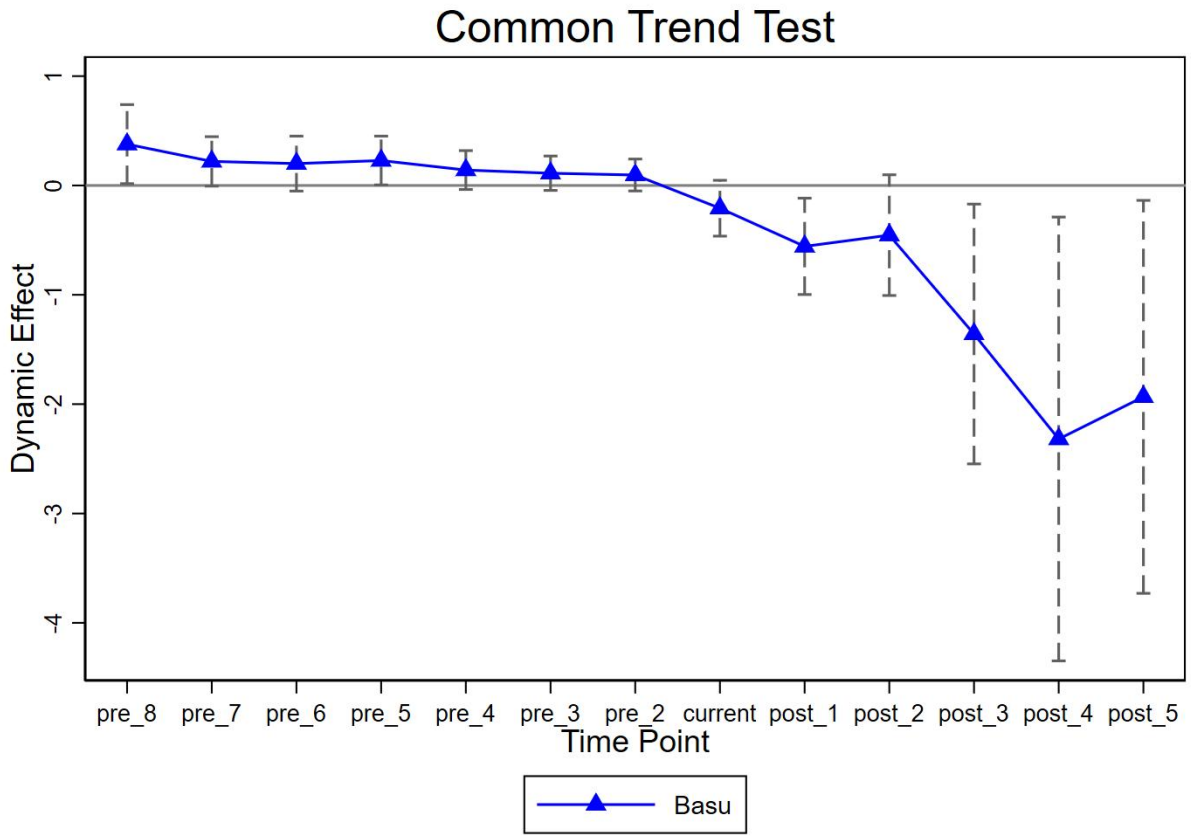


Figure 2 Placebo Test

Figure 2 presents the placebo test results after randomly reset value of independent variables and then regress for 1,000 times. It can be seen that the random sampling coefficient has a mean of 0 and exhibits an approximate normal distribution. In placebo test we also control for firm and year level fixed effect.

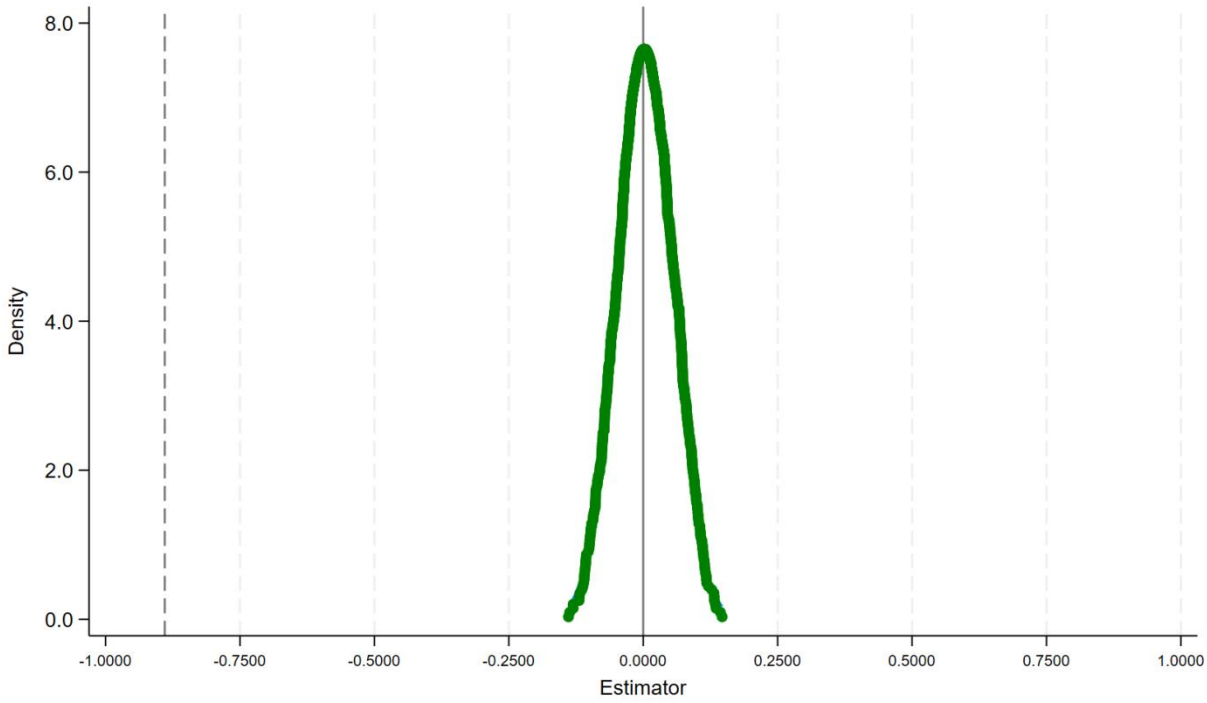


Table 1 Descriptive Statistics & Univariate Analysis

Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Panel A: Descriptive Statistics of Main Variables

Variable	N	Mean	SD	Min	p50	Max
Basu	37,360	1.3312	5.0313	-1.3631	0.0849	27.7088
AIIAPZ	37,360	0.2301	0.4209	0.0000	0.0000	1.0000
Size	37,360	22.3448	1.2958	20.0718	22.1365	26.4065
Growth	37,360	0.1070	0.2963	-0.5562	0.0741	1.4306
Lev	37,360	0.4206	0.2036	0.0570	0.4123	0.8984
ROA	37,360	0.0348	0.0649	-0.2226	0.0352	0.2133
BM	37,360	0.6370	0.2525	0.1268	0.6337	1.2115
Separation	37,360	0.0444	0.0703	0.0000	0.0000	0.2771
Dual	37,360	0.2990	0.4578	0.0000	0.0000	1.0000
Indep	37,360	0.3783	0.0538	0.3333	0.3636	0.5714
Board	37,360	2.1079	0.1969	1.6094	2.1972	2.6391
Top1	37,360	0.3343	0.1482	0.0812	0.3099	0.7383
Balance	37,360	0.9724	0.7995	0.0521	0.7552	3.9617
Big	37,360	0.0661	0.2485	0.0000	0.0000	1.0000
Audit	37,360	0.9740	0.1590	0.0000	1.0000	1.0000

Panel B: Univariate Analysis

Variables	Lower AI Adoption		Higher AI Adoption		Mean_Diff	T Value
	Obs	Mean	Obs	Mean		
Basu	13,542	2.139	23,818	0.872	1.267	23.574***
Size	13,542	22.385	23,818	22.322	0.062	4.471***
Growth	13,542	0.105	23,818	0.108	-0.003	-1.081
Lev	13,542	0.425	23,818	0.418	0.006	2.821***
ROA	13,542	0.032	23,818	0.037	-0.005	-6.944***
BM	13,542	0.651	23,818	0.629	0.022	8.175***
Separation	13,542	0.042	23,818	0.046	-0.003	-4.543***
Dual	13,542	0.299	23,818	0.299	-0.001	-0.105
Indep	13,542	0.379	23,818	0.378	0.002	2.658***
Board	13,542	2.099	23,818	2.113	-0.014	-6.441***
Top1	13,542	0.335	23,818	0.334	0.001	0.710
Balance	13,542	0.967	23,818	0.976	-0.009	-1.028
Big	13,542	0.070	23,818	0.064	0.007	2.456**
Audit	13,542	0.968	23,818	0.977	-0.009	-5.240***

Table 2 Main Results: HDFE Estimator

All specification controlled for Firm, Year and Regional fixed effect to handle the unobservable homogeneity. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficients. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Models	(1)	(2)	(3)	(4)
Variables	Basu	Basu	Basu	Basu
AIIAPZ	-0.8281**	-0.8793**	-0.8894**	-0.8899**
	(-2.39)	(-2.40)	(-2.40)	(-2.41)
Size		-0.0028	-0.0127	-0.0191
		(-0.02)	(-0.07)	(-0.11)
Growth		-0.1697	-0.1704	-0.1703
		(-1.02)	(-1.02)	(-1.02)
Lev		-0.1040	-0.1011	-0.0842
		(-0.16)	(-0.15)	(-0.12)
ROA		-2.0954	-2.0704	-2.1058
		(-1.31)	(-1.32)	(-1.37)
BM		2.0874***	2.0963***	2.0983***
		(2.88)	(2.96)	(2.96)
Separation			-1.8391	-1.8464
			(-1.52)	(-1.52)
Dual			-0.1356	-0.1364
			(-0.98)	(-0.99)
Indep			1.2218	1.2190
			(1.14)	(1.13)
Board			0.3294	0.3252
			(0.72)	(0.72)
Top1			0.2060	0.1973
			(0.21)	(0.20)
Balance			0.0202	0.0195
			(0.14)	(0.14)
Big				0.1744
				(0.80)
Audit				0.0775
				(0.37)
Intercept	1.5048***	0.3863	-0.5227	-0.4584
	(18.94)	(0.10)	(-0.11)	(-0.10)
Year	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*
Obs.	*37,119*	*37,119*	*37,119*	*37,119*
Adj. R^2	*0.328*	*0.332*	*0.332*	*0.332*

Table 3 Heterogeneous Robust DID Estimator

All specification controlled for Firm, Year and Regional fixed effect to handle the unobservable homogeneity. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficients. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Models	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Basu	Basu	Basu	Basu	Basu	Basu
ATT	-0.7625***		-0.7124***		-0.7468***	
	(-5.78)		(-5.84)		(-5.14)	
Pre_avg		0.0009		0.0026		-0.0031
		(0.49)		(1.64)		(-1.09)
Post_avg		-0.8776***		-0.8358***		-0.9166***
		(-4.43)		(-4.40)		(-4.25)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Method	*dripw*		*ipw*		*reg*	
AggType	*Simple*	*Event*	*Simple*	*Event*	*Simple*	*Event*
Obs.	*34,392*	*34,392*	*34,392*	*34,392*	*34,392*	*34,392*

Table 4 Bacon Decomposition

All specification controlled for Firm, Year and Regional fixed effect to handle the unobservable homogeneity. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficients. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Dependent Variables	Basu	
Average Treated Effect	-0.9705***	
	(-5.12)	
Bacon Decomposition	Coefficients	Weight
Timing Groups	-0.13557	4.6264%
Always vs Timing	-0.61814	14.1640%
Never vs Timing	-1.02586	**79.8553%**
Always vs Never	-63.84268	0.0029%
Within	-4.11803	1.3513%

Table 5 Two-stage Least Squares Method

All specification controlled for Firm, Year and Regional fixed effect to handle the unobservable homogeneity. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficients. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Models	(1)	(2)
Variables	AIIAPZ	Basu
AIIAPZ		-2.8387**
		(-2.11)
IV	0.9599***	
	(22.24)	
Controls	Yes	Yes
CD Wald F	*8831.26*	
KP Wald F	*494.64*	
Endogeneity	*P = 0.085*	
KP LM Statistics	*P=0.003*	
Year	*Yes*	*Yes*
Firm	*Yes*	*Yes*
City	*Yes*	*Yes*
Obs.	*37,119*	*37,119*

Table 6 Entropy Balancing Method DID Estimators

All specification controlled for Firm, Year and Regional fixed effect to handle the unobservable homogeneity. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficients. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Panel A: Balancing Tests of Covariates

Covariates	Control Group			Treat Group		
	Obs.	Mean	Std	Obs.	Mean	Std
Size	13,542	22.32291	1.27637	23,818	22.32222	1.27709
Growth	13,542	0.10797	0.28459	23,818	0.10819	0.28420
Lev	13,542	0.41861	0.19946	23,818	0.41833	0.19984
ROA	13,542	0.03657	0.06331	23,818	0.03661	0.06327
BM	13,542	0.62888	0.24755	23,818	0.62893	0.24685
Separation	13,542	0.04553	0.07142	23,818	0.04561	0.07138
Dual	13,542	0.29910	0.45788	23,818	0.29914	0.45789
Indep	13,542	0.37774	0.05383	23,818	0.37774	0.05378
Board	13,542	2.11287	0.19660	23,818	2.11288	0.19703
Top1	13,542	0.33399	0.14913	23,818	0.33392	0.14925
Balance	13,542	0.97511	0.80785	23,818	0.97557	0.80734
Big	13,542	0.06385	0.24449	23,818	0.06373	0.24428
Audit	13,542	0.97717	0.14935	23,818	0.97729	0.14899

Panel B: Entropy Balancing Method

Models	(1)	(2)	(3)	(4)
Variables	Basu	Basu	Basu	Basu
AIIAPZ	-0.8079**	-0.8752**		
	(-2.45)	(-2.46)		
ATT			-0.6694***	
			(-4.40)	
Pre_avg				0.0003
				(0.18)
Post_avg				-0.7173***
				(-3.03)
Controls	No	Yes	Yes	Yes
Intercept	1.6317***	-1.6661		
	(20.77)	(-0.31)		
Year	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*
Obs.	*37,119*	*37,119*	*34,392*	*34,392*
Method			*dripw*	
AggType			*Simple*	*Event*
Adj. R^2	*0.344*	*0.348*		

Table 7 Alternative Measurements of Variables

All specification controlled for Firm, Year and Regional fixed effect to handle the unobservable homogeneity. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficients. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Models	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Basu	Basu	Basu	Basu	Basu	Basu
ATT	-0.8372***			-0.8076***		
	(-5.51)			(-5.74)		
Pre_avg		-3.6779			-3.7416	
		(-0.62)			(-0.65)	
Post_avg		-1.0367***			-1.0151***	
		(-4.43)			(-4.52)	
CAverage			-0.6696***			-0.6462***
			(-5.51)			(-5.73)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Method		*dripw*			*ipw*	
AggType	*Simple*	*Event*	*Calendar*	*Simple*	*Event*	*Calendar*
Obs.	*34,392*	*34,392*	*34,392*	*34,392*	*34,392*	*34,392*

Table 8 Mechanism Tests

All specification controlled for Firm, Year and Regional fixed effect to handle the unobservable homogeneity. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficients. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Panel A: Managerial Predict Capability				
Models	(1)	(2)	(3)	(4)
Variables	Pre_Bias	Basu	Pre_Bias_Mean	Basu
AIIAPZ	-0.0027**	-0.8921**	-0.0031***	-0.8881**
	(-2.31)	(-2.41)	(-3.02)	(-2.42)
Pre_Bias		-0.8000		
		(-1.30)		
Pre_Bias_Mean				0.5924
				(0.47)
Controls	Yes	Yes	Yes	Yes
Intercept	-0.0547***	-0.5022	0.1102***	-0.5237
	(-2.70)	(-0.11)	(7.34)	(-0.11)
Year	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*
Obs.	*37,119*	*37,119*	*37,119*	*37,119*
Sobel Z	*4.902****		*4.890****	
Adj. R^2	*0.235*	*0.332*	*0.345*	*0.332*
Panel B: Managerial Myopia Preference				
Models	(1)	(2)	(3)	(4)
Variables	Myopia_Dis	Basu	Myopia_Inv	Basu
AIIAPZ	0.0026***	-0.8909**	-0.0010**	-0.8907**
	(2.71)	(-2.40)	(-2.45)	(-2.39)
Myopia_Dis		0.3828		
		(0.28)		
Myopia_Inv				-0.7998
				(-0.08)
Controls	Yes	Yes	Yes	Yes
Intercept	0.0981***	-0.4959	-0.0110**	-0.4672
	(5.29)	(-0.11)	(-2.18)	(-0.10)
Year	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*
Obs.	*37,119*	*37,119*	*37,119*	*37,119*
Sobel Z	*4.902****		*2.150***	
Adj. R^2	*0.442*	*0.332*	*0.303*	*0.332*

Table 9 Heterogeneous Analysis: Types of Artificial Intelligence

All specification controlled for Firm, Year and Regional fixed effect to handle the unobservable homogeneity. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficients. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Models	(1)	(2)	(3)	(4)
Variables	Basu	Basu	Basu	Basu
Non_PreAI	0.1571	0.1609		
	(0.53)	(0.57)		
PreAI			-1.1282**	-1.1203**
			(-2.03)	(-2.03)
Controls	No	Yes	No	Yes
Intercept	1.2976***	-0.4770	1.3460***	-0.6219
	(39.28)	(-0.10)	(88.09)	(-0.13)
Year	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*
Obs.	*37,119*	*37,119*	*37,119*	*37,119*
Adj. R^2	*0.327*	*0.331*	*0.327*	*0.331*

Table 10 Heterogeneous Analysis: Bad News Backlog

All specification controlled for Firm, Year and Regional fixed effect to handle the unobservable homogeneity. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficients. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Models	(1)	(2)	(3)	(4)
Group	Lower NCSKEW	Higher NCSKEW	Lower DUVOL	Higher DUVOL
Variables	Basu	Basu	Basu	Basu
AIIAPZ	-0.8949***	-0.8403*	-0.8086***	-0.9406*
	(-2.68)	(-1.74)	(-2.80)	(-1.93)
Controls	Yes	Yes	Yes	Yes
Intercept	-2.2001	-1.8119	0.7878	-2.0066
	(-0.39)	(-0.44)	(0.13)	(-0.46)
Year	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*
Obs.	*18,176*	*18,001*	*18,198*	*18,013*
Adj. R^2	*0.371*	*0.357*	*0.352*	*0.363*

Table 11 Heterogeneous Analysis: Performance Pressure

All specification controlled for Firm, Year and Regional fixed effect to handle the unobservable homogeneity. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficients. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Models	(1)	(2)	(3)	(4)
Group	Lower Current Pressure	Higher Current Pressure	Lower Cumulative Pressure	Higher Cumulative Pressure
Variables	Basu	Basu	Basu	Basu
AIIAPZ	-0.4947*	-1.2751**	-0.3586	-1.1578**
	(-1.72)	(-2.52)	(-1.38)	(-2.51)
Controls	Yes	Yes	Yes	Yes
Intercept	-5.4003	0.6400	-5.6443	1.3039
	(-1.26)	(0.08)	(-1.18)	(0.17)
Year	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*
City	*Yes*	*Yes*	*Yes*	*Yes*
Obs.	*17,850*	*18,012*	*17,708*	*18,064*
Adj. R^2	*0.278*	*0.390*	*0.314*	*0.396*

Appendix A: Distribution and Development of AIIAPZ Regions

City/Province	Approval Time Point (Month-Year)
Pudong/Shanghai	May-2019
Jinan/Shandong	Oct-2019
Qingdao/Shandong	Oct-2019
Shenzhen/Guangdong	Oct-2019
Beijing	Feb-2021
Tianjin/Binhai	Feb-2021
Hangzhou/Zhejiang	Feb-2021
Guangzhou/Guangdong	Feb-2021
Chengdu/Sichuan	Feb-2021
Nanjing/Jiangsu	Oct-2022
Changsha/Hunan	Oct-2022
Wuhan/Hubei	Oct-2022

Appendix B: Variable Definitions Table

Types	Variables	Definitions
Dependent Variable	Basu	A continuous variable which is measured by Basu Model and represents the accounting conservatism according to the sensitivity to bad news in the capital market compared to good news.
Independent Variable	AIIAPZ	A dummy variable which is equals 1 in the year when a firm's headquarters city is designated by the authorities as a artificial intelligence innovation and application pilot zone and in all subsequent years, and 0 otherwise. [MIIT]
Control Variables	Size	A continuous variable which is measured by the natural logarithm of the company's total assets at the end of the year. [Wind]
	Growth	A continuous variable which is measured by the annual revenue growth rate. [Wind]
	Lev	A continuous variable which is measured by the asset-liability ratio. [Wind]
	ROA	A continuous variable which is measured by the net interest rate on total assets. [Wind]
	BM	A continuous variable which is measured by the ratio of a firm's book value to market value. [CSMAR]
	Separation	A continuous variable which is measured by the difference between the cash flow right and voting right of the actual controller of firms. [CSMAR]
	Dual	A continuous variable which is measured by the value is 1 if the CEO and chairman are the same person, otherwise it is 0. [CSMAR]
	Indep	A continuous variable which is measured by the proportion of independent directors in the total number of directors. [CSMAR]
	Board	A continuous variable which is measured by the natural logarithm of the total number of board members. [CSMAR]
	Top1	A continuous variable which is measured by the shareholding ratio of the top one shareholder. [CSMAR]
	Balance	A continuous variable which is measured by the ratio of the shareholding percentages of the second to tenth largest shareholders to that of the largest shareholder. [CSMAR]
	Big	A dummy variable which is equals 1 if the auditing firm of a listed firm is one of the Big Four, and 0 otherwise. [CSMAR]
	Audit	A dummy variable which is equals 1 if the audit opinion of listed firms is standard unqualified opinion, and 0 otherwise. [CSMAR]

Appendix C: Pearson Matrix

Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

	I.Basu	*II.AIIAPZ*	*III.Size*	*IV.Growth*	*V.Lev*	*VI.ROA*	*VII.BM*	*VIII.Separation*	*IX.Dual*	*X.Indep*	*XI.Board*	*XII.Top1*	*XIII.Balance*	*XIV.Big*	*XV.Audit*
I	1.000														
II	0.018***	1.000													
III	-0.020***	0.012**	1.000												
IV	-0.073***	-0.022***	0.015***	1.000											
V	-0.061***	-0.015***	0.477***	0.008	1.000										
VI	-0.044***	-0.030***	0.054***	0.311***	-0.343***	1.000									
VII	0.036***	-0.026***	0.544***	-0.121***	0.345***	-0.165***	1.000								
VIII	-0.003	-0.043***	0.081***	-0.006	0.043***	0.036***	0.052***	1.000							
IX	0.037***	0.038***	-0.183***	0.043***	-0.134***	0.016***	-0.139***	-0.066***	1.000						
X	0.015***	0.036***	-0.010*	-0.006	-0.018***	-0.019***	-0.035***	-0.078***	0.113***	1.000					
XI	-0.041***	-0.058***	0.265***	-0.003	0.140***	0.033***	0.153***	0.068***	-0.190***	-0.568***	1.000				
XII	-0.023***	-0.018***	0.194***	-0.011**	0.028***	0.165***	0.157***	0.172***	-0.070***	0.036***	0.027***	1.000			
XIII	-0.003	0.038***	-0.103***	0.061***	-0.098***	-0.025***	-0.106***	-0.146***	0.077***	-0.028***	0.013***	-0.709***	1.000		
XIV	-0.013**	0.061***	0.336***	-0.005	0.088***	0.039***	0.126***	0.051***	-0.051***	0.038***	0.085***	0.132***	-0.021***	1.000	
XV	-0.003	0.015***	0.055***	0.083***	-0.116***	0.238***	0.033***	0.007	0.014***	0.004	0.014***	0.082***	-0.034***	0.024***	1.000