Two Birds with One Stone:

Artificial Intelligence, Innovation and Corporate Tax Avoidance

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This paper examines the association between the adoption of artificial intelligence and corporate tax avoidance practices among Chinese firms. Utilizing a novel text-based metric to quantify AI adoption, our analysis reveals a positive correlation between AI integration and tax avoidance behaviors. Specifically, a one-standard-deviation increase in AI adoption is associated with a 0.43 percentage point rise in tax avoidance measures. The effect is notably pronounced among smaller firms, those operating in high-tech industries, and those situated in regions with more lenient tax enforcement. Mechanistic investigations suggest that both innovation-driven and cost-related channels contribute to the observed reduction in effective tax rates. Overall, our findings reveals that the adoption of AI not only brings innovation to firms but also results in unexpected tax avoidance effects.

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1 Introduction

Artificial intelligence (AI), heralded as one of the most transformative technological advancements of recent decades, has significantly altered corporate strategies and operations across various industries (Acemoglu and Restrepo, 2018a; Beraja et al., 2023). The swift adoption of generative AI tools has surpassed the pace of prior technological innovations, exemplified by ChatGPT, which amassed one million users within five days of its debut and drew approximately 152 million visitors in its initial month.[3] A 2024 global survey by McKinsey & Company indicates that firms across diverse sectors are actively incorporating generative AI tools into their operations and are committing substantial resources to tailor this technology to their specific needs.[4] Although extensive research has explored the impacts of AI on labor markets, productivity, and innovation (Acemoglu and Restrepo, 2020; Acemoglu et al., 2022; Rammer et al., 2022; Czarnitzki et al., 2023; Babina et al., 2024), the implications for corporate economic behavior remain relatively underexplored. This paper aims to fill this gap by employing an innovative measure of firm-level AI adoption to investigate the economic consequences of artificial intelligence, with a particular focus on the previously underexamined domain of corporate tax avoidance.

Analyzing the relationship between AI adoption and corporate tax avoidance is crucial due to its significant financial ramifications. Firms may leverage the use of AI to minimize their tax liabilities, and reallocate the resultant tax savings to other strategic investments, such as mergers and acquisitions, or market expansion, thereby enhancing their growth trajectory and competitive positioning (García-Manjón et al., 2012; David, 2021). However, pervasive AI-related tax avoidance practices could undermine government revenues, thereby influencing public spending and fiscal policy (Compagnie et al., 2023). A comprehensive understanding of the scope and characteristics of such behaviors can enable policymakers to better anticipate and address potential revenue shortfalls.

However, the theoretical impact of AI adoption on firms' tax avoidance strategies

[3] Source: BIS Annual Economic Report 2024. https://www.bis.org/publ/arpdf/ar2024e3.htm
[4] https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

remains ambiguous. On one hand, the integration of artificial intelligence can bolster investment in research and development (R&D) and stimulate innovation (Babina et al., 2024), which may qualify firms for tax incentives such as credits and deductions (Gao et al., 2016). Firms might leverage these incentives to reduce their tax liabilities and achieve lower effective tax rates. On the other hand, AI can improve transparency and automate tax compliance processes (Morse, 2020; Fedyk et al., 2022), potentially curtailing aggressive tax avoidance practices. Currently, theoretical evidences regarding this relationship are mixed, underscoring the necessity for further investigation to elucidate the impact of AI on corporate tax avoidance behaviors.

This paper explores the interaction between AI adoption and corporate tax avoidance within the context of China, the world's largest developing economy. The Chinese government has positioned AI as a cornerstone of its national strategy, with the objective of becoming a global leader in AI by 2030. Over the past decade, China has invested tens of billions of dollars in AI development, and this technology has been integrated across various sectors, including education, healthcare, finance, manufacturing, transportation, and retail. Simultaneously, while China's tax enforcement environment has seen improvements, it has traditionally offered some degree of leniency towards corporate tax avoidance (Li et al., 2022). This combination of rapid technological advancement and a relatively permissive tax enforcement regime creates a distinctive setting to investigate the dynamics between AI adoption and tax avoidance.

In this study, we leverage the framework established by Yao (2024) to analyze the impact of AI adoption on corporate tax avoidance, utilizing machine learning techniques to develop a comprehensive AI lexicon. We apply this lexicon to conduct a textual analysis of the annual reports of Chinese listed firms, thereby constructing firm-specific AI indicators. Our findings indicate a statistically significant relationship between AI adoption and increased levels of tax avoidance. Specifically, a one-standard-deviation increase in the intensity of AI adoption is associated with a 0.43 percentage point rise in tax avoidance metrics. This result is robust across various sensitivity analyses, including propensity score matching, instrumental variable approaches, alternative measures of tax avoidance, and different AI indicators.

We further investigate cross-sectional variables that modulate the effect of AI adoption on tax avoidance. Our heterogeneous analysis reveals that the relationship between AI adoption and tax avoidance is more pronounced in smaller firms, those operating in high-tech sectors, and companies situated in regions with weaker tax enforcement. Mechanistic insights indicate that AI investment amplifies expenditure on research and development and fosters innovation, leading to lower effective corporate tax rates due to the tax benefits associated with research and development costs and patent income. Additionally, while AI enhances productivity, it also escalates initial capital and labor costs, which incentivizes firms to engage in tax avoidance to conserve cash resources.

This study advances the discourse at the intersection of artificial intelligence (AI), economics, and accounting—an area currently at the forefront of academic inquiry. While extant literature predominantly addresses the macroeconomic implications of AI, including its impacts on labor market dynamics (Acemoglu and Restrepo, 2018a; 2018b; 2019), productivity (Czarnitzki et al., 2023), and economic growth (Goldfarb et al., 2023), there remains a significant gap in understanding AI's effects at the firm level. Previous attempts to measure firm-level AI investments through employee resumes (Fedyk et al., 2022; Babina et al., 2024) have been constrained by limited data availability and lack of generalization. This paper offers a novel approach by constructing firm-specific AI indicators derived from textual analysis of annual reports of publicly listed companies, thereby validating and extending the methodology proposed by Yao (2024). Our work provides a robust framework for future research into the microeconomic implications of AI adoption.

This paper presents the first causal evidence of the substantial impact of AI adoption on corporate tax planning. It is particularly pertinent for corporations assessing the trade-offs between the costs of AI investment and its potential benefits.

Although prior research has investigated various dimensions of AI's influence on corporate financial and accounting outcomes, including auditing quality (Fedyk et al., 2022), loan underwriting (Jansen et al., 2020), analyst forecasts (Cao et al., 2024), and corporate disclosure (Cao et al., 2023), our study is pioneering in examining whether increased AI adoption leads to greater corporate tax avoidance. Our findings highlight that firms adopting AI leverage associated tax benefits to achieve significantly lower effective tax rates. The dual advantages of enhanced innovation and reduced tax liabilities position AI adoption as a strategically attractive approach for firms aiming to boost their competitiveness while optimizing tax outcomes.

The remainder of this paper is organized as follows. Section 2 delineates the theoretical framework and develops the associated hypotheses. Section 3 addresses methodological considerations, encompassing data sources, sample characteristics, and variable definitions. Section 4 presents the baseline results, along with robustness checks and cross-sectional analyses. Section 5 explores the underlying mechanisms driving the observed effects. Finally, Section 6 offers concluding remarks.

2 Theoretical framework and hypothesis development

Artificial intelligence encompasses a broad array of computer systems designed to perform tasks traditionally requiring human-like cognitive abilities. The emergence of deep learning and large language models has propelled AI into the forefront of both academic and commercial discourse. As a predictive technology, AI excels in analyzing large datasets and enhancing the efficiency of learning processes, thereby unlocking new business opportunities for firms (Agrawal et al., 2019). For instance, AI has the potential to accelerate the drug development life cycle significantly. Unlike technologies that primarily demand capital investment, such as industrial robots, AI complements human expertise and contributes to the creation of intangible capital within firms (Benmelech and Zator, 2022). By integrating seamlessly into firms' decision-making processes, AI functions as a general-purpose technology (GPT), applicable across various business segments and sectors to address a diverse array of business challenges.

The impact of AI investment on firms' tax planning remains an open question, with two competing hypotheses regarding its effects. On one hand, AI may catalyze innovation, potentially prompting firms to engage in tax avoidance by exploiting tax credits associated with innovative activities. On the other hand, AI could enhance quality of internal control and automate compliance processes, thereby aiding firms in making more informed decisions regarding tax planning and potentially reducing aggressive tax strategies. We discuss the theoretical underpinnings and predictions associated with these two contrasting channels below.

2.1 Innovation theory, artificial intelligence and tax avoidance

It is plausible that corporate tax avoidance could rise as firms invest in AI technology. According to Schumpeterian innovation theory, economic advancement is primarily driven by creative destruction, where new innovations replace obsolete technologies and processes. AI is instrumental in this process by fostering experimentation and reducing the costs associated with innovation, thus accelerating creative destruction (Bustamante et al., 2022). By enhancing the pace of knowledge accumulation and lowering entry barriers for new innovations, AI expedites technological progress (Babina et al., 2024).

To stimulate firm-level innovation, governments worldwide have enacted various R&D tax policies (Gao et al., 2016). For example, the United States initially introduced the R&D tax credit as a temporary measure in 1981, and it was later made a permanent component of the tax code through the Protecting Americans from Tax Hikes Act of 2015. In China, firms involved in R&D activities that yield technological advancements are entitled to deduct between 150% and 200% of their qualifying R&D expenses from taxable income, effectively allowing companies to claim 1.5 to 2 RMB for every RMB spent on eligible R&D activities. Additionally, several European Union countries and China have implemented patent box regimes, in which revenue generated from patents developed through a firm's own research is eligible for preferential tax treatments (Haufler and Schindler, 2023).

Tax credits for innovation activities have the potential to substantially lower firms' effective tax rates, which can incentivize tax avoidance behaviors (Cheng et al., 2021). By offering these credits, policymakers aim to encourage research and development and technological advancement. However, firms may strategically use these credits to reduce taxable income and overall tax burdens, sometimes beyond the intended scope of innovation. This form of tax minimization could potentially dilute the policy's objective by shifting the focus from genuine R&D investments to aggressive tax planning.

Another justification for tax aggressiveness arises from the significant capital outlay required for AI investments, which can elevate operating costs and heighten financial pressures. This may lead firms to adopt additional tax avoidance strategies to relieve these economic burdens. In highly competitive markets, firms often face difficulty passing increased costs onto consumers without impacting profit margins (Chava et al., 2023). As a result, the financial burden from substantial AI investment generally remains with the firms themselves. Trade-off theory suggests that financially constrained firms prioritize internal financing over external sources (Kraus and Litzenberger, 1973; Fama and French, 2002; Van Binsbergen et al., 2010). In this context, tax avoidance can act as a complementary form of internal financing, implying that firms with higher AI-related investment demands may engage in more aggressive tax planning.

On the basis of this rationale, we construct our first hypothesis as follows:

H1a: *The adoption of artificial intelligence leads to greater corporate tax aggressiveness.*

2.2 Agency theory, artificial intelligence and tax avoidance

Conversely, existing literature suggests that AI adoption may lead to a reduction in corporate tax avoidance. Agency theory, which highlights conflicts of interest between agents and principals (Jensen and Meckling, 1976; Eisdorfer, 2008), implies that executives might engage in tax avoidance to enhance short-term gains or personal benefits, potentially conflicting with the long-term interests of shareholders. AI, as an automation technology, enhances internal controls within firms (Fedyk et al., 2022;

Ashraf et al., 2024), thereby aligning executive actions more closely with shareholder interests and potentially mitigating tax avoidance behaviors.

Internal control encompasses the processes and procedures designed by firms to ensure the accuracy of financial reporting, compliance with laws, and effective operational management (Bauer, 2016). The adoption of artificial intelligence technology mitigates human-related issues such as forgetfulness, errors, discretion, and fraud in financial reporting. Given that human factors are prominent sources of failure in internal controls (Ashraf et al., 2024), AI-enhanced financial reporting strengthens these controls and reduces agency conflicts, which can decrease tax aggressiveness (Grennan and Michaely, 2020). Moreover, AI improves tax compliance by automating data processing and real-time monitoring, thereby minimizing errors and ensuring adherence to regulatory requirements. The predictive analytics and error detection capabilities of AI facilitate proactive tax management and risk mitigation.

Taken together, the adoption of AI aims to mitigate conflicts of interest and ensure that managerial decisions align with the best interests of shareholders. Based on this rationale, we anticipate that AI technology may lead to a reduction in corporate tax aggressiveness. Consequently, we propose the following alternative hypothesis:

H1b: *The adoption of artificial intelligence leads to lower corporate tax aggressiveness.*

3 Data and key variables

3.1 Data

Our dataset is drawn from the Wind and CSMAR databases, both of which are well-established sources for financial data on the Chinese market. To examine the impact of AI adoption on corporate tax planning, our sample covers a 17-year period from 2007 to 2023. We selected 2007 as the starting year because the surge in AI development can be traced back to the introduction of deep learning algorithms in 2006, which represented a significant technological advancement. Therefore, the adoption of AI by companies likely became more pronounced starting in 2007. We have chosen 2023 as the end of our sample period to utilize the most recent available data.

We further refine our sample using the following criteria: (1) exclusion of financial firms; (2) exclusion of firms in the information technology and scientific research sectors, as these industries inherently utilize AI technology and disclose related information, complicating the assessment of AI adoption's impact on their operations; (3) exclusion of firms with non-positive accounting profits. To mitigate the effects of outliers, all continuous variables are winsorized at the 1% and 99% levels. After applying these screening procedures, our final sample consists of 34,307 firm-year observations from 4,144 firms for the empirical analysis.

3.2 Independent variables: AI adoption

In alignment with the methodology established by Yao et al. (2024), we introduce a firm-level metric for AI adoption by analyzing the prevalence of AI-related terminology within annual reports of firms. Specifically, we examine the annual reports of Chinese publicly listed firms to identify their utilization of artificial intelligence technologies. Table A1 in Appendix A provides illustrative examples of the raw data utilized in this analysis. Utilizing machine learning techniques, we developed an AI lexicon consisting of 73 distinct keywords, which enables the construction of corporate AI index from the textual content of these reports.[5] Our primary measure, denoted as the AI Index, is defined as *AI Index* = *Ln*(1+*Words*), where *Words* represents the count of AI-related keywords within the firms' annual reports. A comprehensive methodology for the development of this measure is detailed in Appendix B.

3.3 Dependent variable: tax avoidance

We utilize the difference between statutory and effective tax rates (hereafter referred to as DTR) as an indicator of corporate tax avoidance, a methodology consistently employed in the extant literature (Inger, 2014; Chan et al., 2016). The effective tax

[5] The list of 73 AI-related keywords is displayed in Table B1.

rate may be diminished due to either preferential tax treatments specific to certain jurisdictions or industries or through deliberate tax avoidance strategies implemented by firms (Shevlin et al., 2012). The DTR metric enables us to isolate a firm's tax avoidance behavior by controlling for the effects of such preferential tax rates. A positive DTR value implies the presence of tax avoidance activities, with greater values reflecting higher degrees of tax aggressiveness.

3.4 Control variables

We incorporate several control variables to account for factors that may influence firms' tax planning activities. To address variations in firm size, we include total assets (*Size*) as proposed by Chyz et al. (2013), Fairhurst et al. (2020), and Wang (2023; 2024). Additionally, financial leverage (*Lev*) is controlled for, given its role in driving corporate tax avoidance through tax shields (Omer et al., 1993). We also account for firm profitability (*ROA*), as higher earnings might incentivize more aggressive tax strategies. To differentiate between accounting and taxable profits, we include fixed assets (*PPE*), intangible assets (*Intangibles*), and research and development expenses (*R&D*) as control variables (Laplante et al., 2019). Cash flow (*Flow*) is added to capture the impact of liquidity on tax planning, under the assumption that firms with higher cash reserves are less reliant on tax deferrals (Atawnah et al., 2020). Sales growth (*Growth*) is included as a proxy for growth opportunities. To address the influence of international operations on tax planning (Dyreng and Lindsey, 2009; De Waegenaere et al., 2012; Liu, 2013), we introduce a dummy variable indicating foreign income (*FI*). Additionally, equity income (*EQINC*) is included to account for differences between accounting and taxable profits due to income from unconsolidated entities (Dyreng et al., 2010). Detailed definitions of these key variables are provided in Appendix C.

3.5 Stylized facts and descriptive statistics

We utilize a firm-level AI index to examine the adoption of artificial intelligence technology across various firms and industries. Initially, we aggregate firm-level data to a cross-sectional level by calculating the proportion of firms exhibiting a positive

AI index. Our analysis reveals a substantial increase in AI adoption. As illustrated in the solid line in Panel (a) of Figure 1, the average fraction of firms adopting AI technology escalated from 1.4% in 2007 to 64% by 2023. The dashed line illustrates the trend in the AI index, highlighting a notable upward trajectory over time.

Furthermore, we observe an intuitive distribution of AI adoption across industries. Panel (b) of Figure 1 depicts the average share of firms adopting AI within each major sector, comparing the periods 2007-2014 and 2015-2023. Notably, the education sector demonstrates the highest AI adoption rates, increasing from 26.7% during the earlier period to 79.6% in the later period. This increase is largely driven by the reliance of online education firms on AI for personalized learning and content creation, enhancing the efficiency and effectiveness of educational delivery. Despite this sectoral variation, nearly all sectors experience a significant rise in AI adoption, supporting the notion of AI as a general-purpose technology (Goldfarb et al., 2023). The comprehensive nature of our text-based approach underscores its effectiveness in capturing AI adoption across a broad spectrum of economic sectors.

Additionally, we present summary statistics for the AI index and the tax avoidance variable in our study. Table 1 illustrates significant variation in the AI index across firms, with a mean value of 0.674 and a standard deviation of 1.043. This variation is substantial, providing the necessary diversity to analyze the relationship between AI adoption and firm outcomes. The tax avoidance measure, DTR, has a mean value of 1.975% and a median value of 1.559%. These figures indicate that tax avoidance is relatively common among Chinese firms, consistent with findings from prior research (Li et al., 2022).

Table 1 also provides summary statistics for additional key variables. Firm size, represented by the logarithm of total assets, has a mean value of 8.33. The average firm leverage stands at 0.41, indicating that, on average, 41% of firms' book assets are financed by debt. The mean value for *PPE* is 0.22, suggesting that fixed assets constitute 22% of book assets on average. Intangible assets and R&D expenses exhibit mean values of 0.04 and 0.02, respectively, indicating that these components represent a relatively minor portion of book assets. Firms generally experience a double-digit revenue growth rate, with a mean value at 16%. Additionally, most firms are profitable, as evidenced by a median value of ROA at 5.5%, and exhibit positive cash flow. Approximately 60% of the firms have foreign income (mean *FI* = 0.65), while 37% report equity income from unconsolidated entities.

Before moving to our empirical model, we present a binned scatterplot of the tax avoidance measure against the AI index in Figure 2. The fitted line shows an upward slope, indicating a positive relationship between the AI index and DTR. Then we proceed to the model part.

4 Model and results

4.1 Model Specification

In this section, we outline our baseline ordinary least squares (OLS) regression model, which examines the relationship between firms' tax avoidance behavior and measures of AI adoption. Our analysis explores the effect of AI adoption on corporate tax planning while accounting for fixed effects at the firm, province, industry, and year levels. Additionally, we control for various firm-specific characteristics to ensure a comprehensive assessment of the relationship.

The specification of the regression is as follows:

$$DTR_{it} = \alpha_0 + \alpha_1 AI_{it} + \beta X_{it} + \kappa_i + \delta_{st} + \varphi_{pt} + \varepsilon_{it} \qquad (1)$$

where DTR_{it} proxies for tax avoidance, defined as the difference between statutory and effective tax rates, for firm i in year t. AI_{it} is the AI index measure for firm i in year t. X_{it} represents the set of control variables, including firm size, financial leverage, *PPE*, intangibles asset, *R&D*, *ROA*, cash flow, revenue growth, foreign income and equity income. The firm-fixed effect, κ_i, controls for time-invariant firm characteristics. We also include industry-year fixed effect, δ_{st}, to capture the industry-specific shock in each period, and include province-year fixed effect, φ_{pt}, to capture the province-specific shock in each year. ε_{it} is the error term with standard errors clustered at the firm level.

4.2 Baseline results

Table 2 presents the estimated effects of AI technology adoption on firms' tax aggressiveness. The results are reported across three columns, each incorporating different sets of fixed effects. Column 3, which represents the preferred specification, includes firm-level controls and a comprehensive set of fixed effects.

In all model specifications, AI adoption is found to have a statistically significant positive effect on firms' tax avoidance at the 1% significance level. Specifically, the coefficient of 0.455 in column 1 indicates that a one-standard-deviation increase (1.043) in AI levels is associated with an approximate 0.47 percentage point (0.455*1.043) increase in corporate tax aggressiveness. Additionally, the results in column 3 show that a one-standard-deviation increase in AI levels corresponds to a 0.43 percentage point (0.411*1.043) rise in corporate tax avoidance. This effect represents 21.8% (0.43/1.975) of the sample mean (1.975%) of the dependent variable.

Overall, the empirical evidence robustly supports our hypothesis (H1a), suggesting that the adoption of AI technology is associated with increased tax avoidance.

4.3 Robustness analysis

In this subsection, we conduct various sensitivity analyses to test the robustness of our baseline results, including 1) instrumental variable estimates, 2) additional approach on addressing endogeneity, 3) propensity score matched sample estimation; 4) alternative definitions of tax avoidance, 5) alternative measure for AI adoption.

4.3.1 Instrumental Variable Estimates

To develop our instrumental variable, we utilize the historical designation of a city as a treaty port (*PORT*) between 1840 and the end of the Qing Dynasty (Jia, 2014). This historical designation is expected to have facilitated the adoption of advanced technologies by local firms, without directly impacting their contemporaneous tax planning, thereby meeting the relevance and exogeneity criteria for an effective instrumental variable. We operationalize *PORT* as a binary variable, where *PORT* equals 1 if the city was a treaty port during the specified period and 0 otherwise.

Given that the treaty port status is invariant over time while our dataset includes firm-year panel data, we incorporate temporal variation by using the annual number of global artificial intelligence patent applications as a time-varying measure, serving as a proxy for the global development of AI technology. This measure is posited to affect firm productivity solely through its influence on the advancement of AI technology.

Thus, the interaction term between a city's treaty port status and the natural logarithm of the number of global AI patent applications in the preceding year constitutes a suitable instrumental variable, satisfying the criteria for relevance and exogeneity. Our instrumental variable is constructed as the interaction term ($PORT \times GlobalAI$), where *PORT* denotes the treaty port status and *GlobalAI* represents the natural logarithm of global AI patent applications from the previous year.

Table 3 presents the results from the two-stage least squares (2SLS) estimation. In the first stage, the coefficient on the instrumental variable ($PORT \times GlobalAI$) is 0.030 and statistically significant at the 1% level. The Cragg-Donald Wald F statistic significantly surpasses the critical values proposed by Stock and Yogo (2002), indicating no weak instrument issues. The second-stage regression results reveal a significantly positive coefficient for the Instrumented AI Index, affirming the robustness of the study's findings.

4.3.2 Additional Method at Addressing Endogeneity

To address endogeneity issues stemming from potential omitted variable bias, we employ the methodologies outlined by Altonji et al. (2005) and Oster (2019) to assess the impact of unobserved selection bias.

Following the approach of Altonji et al. (2005), we first examine the selection on the observables to evaluate the extent to which our estimates might be influenced by the unobserved characteristics across firms. Specifically, let β_L denote estimated coefficient for *AI Index* in a regression that includes only *AI Index*, along with firm, industry-year, and province-year fixed effects (see column 1 of Table 4). Let β_F

represent the estimated coefficient for *AI Index* in a regression that incorporates *AI Index* along with all controls variables and fixed effects (see column 2 of Table 4). The ratio $\left|\beta_F/(\beta_L-\beta_F)\right|$ quantifies the degree of selection bias, where a higher ratio suggests a greater selection effect needed to nullify the estimated coefficient. The results in column 2 indicate that the selection on unobservable variables would need to be at least 4.52 times as significant as selection on observable variables to reduce the estimated effect to zero (approximately |0.411/(0.320-0.411)|). Given that this ratio is substantially greater than zero, our concern about selection bias due to unobservables is mitigated.

However, as Oster (2019) notes, it is crucial to evaluate variations in coefficients in conjunction with changes in *R*-squared to assess the robustness of our estimates. Specifically, if the model approaches the upper bound of the *R*-squared, which represents the R-squared from a model incorporating both all observable and unobservable variables affecting the outcome, concerns regarding omitted variable bias would be significantly mitigated. Let $R_{\max}$ denote the upper limit for the *R*-squared, corresponding to a model that includes the *AI Index* and all observable and unobservable variables. Let R_F represent *R*-squared from a model that includes the AI Index along with all controls and fixed effects (column 2 of Table 4), while R_L corresponds to the R-squared from a model with a more limited set of variables (column 1 of Table 4). Additionally, let $\delta\in[0,1]$ denote the assumed ratio of selection-on-unobservables to selection-on-observables.

By comparing R_F and R_L with $R_{\max}$, we can gauge the extent to which the inclusion of additional variables addresses the potential omitted variable bias. This comparison helps us understand the degree to which the observed coefficient variations are driven by unobservable factors.

The effect of AI adoption on corporate tax avoidance is constrained by $\beta^*(R_{\max},\delta)=\beta_F-\delta(\beta_L-\beta_F)\dfrac{R_{\max}-R_F}{R_{\max}-R_L}$. According to Oster (2019), the maximum achievable R-squared is set to $R_{\max} = \min\{1.3R_F, 1\}$ and the ratio of selection-on-unobservables to observables is set at $\delta = 1$. Given these parameters, the estimated causal impact is anticipated to fall within the interval between β_F and β^*. Panel B of Table 4 demonstrates that the estimated range of the impact is [0.411, 0.490]. This range is distinctly above zero, indicating that the causal effect of AI adoption on corporate tax avoidance is both statistically significant and robust against potential selection bias.

4.3.3 Propensity Score Matched Sample Estimation

The adoption of artificial intelligence by firms is not an exogenous phenomenon but is instead influenced by firm-specific attributes such as human capital, management practices, and technological capability, in addition to shifts in the external environment. As a result, empirical analyses may encounter issues related to sample self-selection bias. To mitigate this potential endogeneity, the present study employs the Propensity Score Matching (PSM) technique. Specifically, firms are categorized into a treatment group and a control group based on the presence or absence of AI-related keywords in their annual reports. Control variables from baseline regressions serve as matching criteria, with nearest neighbor matching conducted at ratios of 1:3, 1:4, and 1:5.

Next, we assess the effectiveness of the matching process through a balance test. For instance, Figure D1 shows the propensity score distributions before and after matching for the 1:5 nearest-neighbor case. A visual comparison indicates that PSM effectively reduces the bias between the treatment and control groups. Additionally, Figure D2 highlights the differences in covariates before and after matching, demonstrating that the deviations in majority of the control variables decrease to less than 5%, confirming that the balance hypothesis holds. Similar results are observed for the 1:3 and 1:4 matching scenarios.

Results for the matched samples, as detailed in Table 5, demonstrate the robustness of our findings, effectively addressing concerns related to self-selection bias.

4.3.4 Alternative measures for tax avoidance

In our previous analyses, we utilized *DTR* as a proxy for corporate tax avoidance. To further validate the robustness of our findings, we now incorporate two alternative measures of tax aggressiveness. The first alternative measure is the book-tax difference (thereafter, *BTD*), defined as the difference between pretax accounting profit and taxable income, scaled by total assets (Desai and Dharmapala, 2006, 2009; Wilson, 2009). Higher *BTD* values signify increased tax aggressiveness. The second alternative measure is the effective tax rate (ETR), calculated as income tax expenses divided by pretax accounting profit (Hanlon and Heitzman, 2010; Kim et al., 2022). Lower *ETR* values denote higher tax avoidance.

As presented in Table 6, the estimates derived from these alternative measures substantiate our primary findings across all specifications. Specifically, increased adoption of AI technology is associated with elevated tax avoidance levels. In column 1, where *BTD* serves as the dependent variable, a one-standard-deviation increase in the AI Index is linked to a 0.16 percentage point (0.155*1.043) increase in tax aggressiveness. Given that the mean *BTD* is 1.42 percent, this corresponds to an approximate 11% increase relative to the sample mean. Similarly, in column 2, with *ETR* as the dependent variable, a one-standard-deviation increase in *AI Index* results in a 0.56 percentage point (0.401*1.043) reduction in the effective tax rate. The magnitudes of the coefficients from these alternative measures align closely with those observed in our baseline results presented in Table 2. Collectively, these findings reinforce the positive relationship between AI adoption and tax aggressiveness, corroborating our baseline conclusions.

4.3.5 Alternative measures for Adoption of AI

To assess the robustness of our results with respect to alternative metrics of AI adoption, we undertake several supplementary analyses. Initially, we develop a binary indicator derived from the AI Index variable utilized in the primary analysis. This indicator is assigned a value of one if AI-related keywords are detected in firms' annual reports, and zero otherwise. Additionally, we propose a secondary measure of

AI adoption by examining the frequency of AI-related keywords within the Management Discussion and Analysis (*MD&A*) sections of the annual reports of publicly traded firms. This measure is quantified as the natural logarithm of one plus the count of AI-related keywords present in the *MD&A*. The empirical results presented in Table 7 corroborate our initial findings, demonstrating that increased AI technology adoption is positively associated with enhanced tax aggressiveness.

4.4 Heterogeneous analysis

In this subsection, we extend our analysis to explore the differential impact of tax avoidance across various firm characteristics. We conduct a series of heterogeneous analyses focusing on three key dimensions: (1) firm size, (2) industry-specific differences, and (3) variations in the tax enforcement environment.

4.4.1 Firm Size

We investigate how tax aggressiveness varies with firm size, drawing on existing literature that suggests smaller firms are generally more adept at adopting AI and thus experience more immediate benefits from its implementation (Brynjolfsson et al., 2023). Smaller firms are often characterized by greater agility, fewer bureaucratic impediments, and more streamlined decision-making processes, which facilitate the effective integration of AI. Consequently, these firms can achieve significant gains in productivity and efficiency, positioning them to quickly capitalize on technological advancements. Based on this rationale, we hypothesize that the effect of AI adoption on tax avoidance will be more pronounced in smaller firms.

To test this hypothesis, we categorize firms into two groups based on their size, as measured by total assets at the end of 2023. Firms are classified as large or small depending on whether their asset values are above or below the sample median, respectively. We then re-estimate the difference-in-differences model specified in Equation (1) for each size group. Panel A of Table 8 reveals that the impact of AI adoption on tax aggressiveness is indeed more substantial for smaller firms. Specifically, the coefficient for the small firm group, reported in column 2, is significantly larger than that for the large firm group in column 1, with the difference being statistically significant at the 5% level (p-value = 0.017). This suggests that small firms derive greater tax avoidance benefits from the adoption of AI technology.

4.4.2 Industry Heterogeneity

The effect of artificial intelligence on tax avoidance may differ across various industries. In high-tech sectors, technological innovation is pivotal to competitive advantage. Compared to their low-tech counterparts, high-tech industries typically employ a larger proportion of highly skilled workers, utilize more advanced technologies and knowledge, and engage in more rapid research and development. Consequently, AI can more effectively leverage these high-skilled labor forces to drive innovation in high-tech industries, potentially amplifying its impact on tax avoidance.

To examine these industry-specific effects, we divide the full sample into two groups: high-tech and low-tech industries. Panel B of Table 8 presents the results of this analysis. The coefficient for the AI Index is significantly higher for the high-tech group compared to the low-tech group, with the difference reaching statistical significance at the 5% level. This finding suggests that the tax avoidance benefits of AI are more pronounced in high-tech industries. It further supports the notion that AI, by complementing skilled labor and fostering innovation, facilitates greater tax advantages for firms in high-tech sectors.

4.4.3 Tax enforcement

We analyze the variation in the impact of AI adoption on corporate tax avoidance contingent on the stringency of tax enforcement. In jurisdictions with stringent tax enforcement, firms face elevated legal risks, thereby incurring higher marginal costs associated with tax avoidance (Atwood et al., 2012; Hoopes et al., 2012). Consequently, we hypothesize that AI adoption will have a reduced effect on corporate tax planning for firms situated in regions with more rigorous tax enforcement.

To examine this hypothesis, we categorize firms into two groups based on the legal environmental index for 2023, as developed by Fan et al. (2011). This index measures the judicial quality across provinces, with higher scores indicative of stricter tax enforcement (Cui et al., 2018). Firms in provinces with an above-median Legal Environmental Index are designated as the strict enforcement group, while those in provinces with below-median scores are classified as the lax enforcement group. The empirical results presented in Panel C of Table 8 indicate that the effect of the adoption of AI technology on tax avoidance is more pronounced and statistically significant for firms in regions characterized by lax tax enforcement, as compared to those in regions with stringent enforcement. The disparity in the coefficients between these subsamples is statistically significant (p-value = 0.002). These findings underscore the pivotal role of effective tax enforcement in moderating firms' tax avoidance behaviors and highlight the necessity of robust enforcement mechanisms in reducing tax avoidance practices.

5 Mechanism analysis

Thus far, we have provided compelling evidence indicating that the adoption of AI technology is associated with heightened corporate tax aggressiveness. To further elucidate this relationship, we investigate potential mechanisms underlying this effect. First, we analyze the innovation channel. Our findings suggest that the adoption of artificial intelligence is linked to increased expenditure on research and development and a subsequent rise in corporate innovation. This enhanced innovation activity appears to result in reduced tax liabilities for firms. Second, we consider other possible channels. Specifically, we find evidence that the increase in operating costs associated with AI technology contributes to the observed increase in tax aggressiveness. Finally, we exclude alternative channels related to quality of internal control.

5.1 Innovation channel

Prior research has established that artificial intelligence catalyzes corporate innovation. As a predictive technology, AI enhances the efficiency of the learning process, integrates directly into products, and customizes offerings to consumer preferences (Babina et al., 2024). To foster innovation, governments provide tax incentives for firms engaged in research and development and patent acquisition, which significantly lower effective corporate tax rates.

Under current Chinese tax legislation, firms are allowed to deduct 100% of eligible R&D expenses from their taxable income. Furthermore, they may benefit from a super deduction, which permits an additional 75% or 100% deduction on eligible R&D expenditures, contingent upon specific criteria. This effectively reduces taxable income and, consequently, lowers the firm's effective tax rate. Additionally, China's patent box system provides a substantial reduction in the corporate tax rate on revenue derived from qualifying intellectual property (Gao et al., 2016).

To empirically assess these dynamics, we utilize firm-level patent data from the State Intellectual Property Office (SIPO) in China, integrating it with our primary dataset. We investigate corporate innovation through the model specification outlined in Equation (1). Initially, we analyze whether firms adopting AI exhibit increased R&D investment, as proxied by the ratio of R&D expenditure to lagged assets. Column 1 of Table 9 presents evidence that AI adoption is associated with a rise in R&D investment. Specifically, a one-standard-deviation increase in the AI Index correlates with approximately a 4.5% increase in the sample mean of R&D investment metrics.

Subsequently, Columns 2 and 3 reveal a positive relationship between AI adoption and patent activity. A one-standard-deviation increase in the AI Index corresponds to approximately 4.4% and 6.6% increases in the number of patents applied for and patents granted, respectively. Finally, Columns 4 and 5 examine the impact of AI adoption on the quality and efficiency of innovation. Using patent citations as a measure of innovation quality and patents granted per R&D expenditure as a proxy for innovation efficiency, the results indicate that AI adoption significantly enhances both innovation quality and efficiency. Collectively, these findings underscore that firms leveraging AI are advancing their R&D and innovation activities, consistent with our hypothesis and reflecting AI's primary role in product development and enhancement.

5.2 Cost channel

We proceed to examine whether initial investments in AI technology influence corporate costs and productivity. Existing literature has demonstrated that AI can foster technological innovations aimed at reducing operating costs and enhancing productivity (Basu et al., 2001; Acemoglu et al., 2020). However, the initial financial outlay required for investing in general-purpose technologies may impose a significant short-term financial burden on firms, potentially prompting them to adopt cash-saving strategies such as tax aggressiveness.

Table 10 presents the results of our analysis. Columns 1 and 2 assess the impact of AI investment on corporate costs, employing two different proxies for operating costs: the cost of goods sold (COGS) relative to sales, and the net profit margin, which is the ratio of net profit to sales. Our findings indicate that initial investments in AI technology are associated with increased costs and reduced profitability for firms. Column 3 explores the effect of AI investment on financial constraints, using the Kaplan-Zingales (KZ) index as a proxy. The significantly positive coefficient for the AI index suggests that AI investment exacerbates firms' financial burdens, indicating greater financial constraints.

Finally, Column 4 investigates the impact of AI investment on productivity, proxied by total factor productivity (TFP) as calculated using the method of Levinsohn and Petrin (2003). We find that AI adoption leads to improvements in productivity, consistent with the findings of Czarnitzki et al. (2023). However, these productivity gains may be partially offset by the increased operating costs, which intensify financial pressures on firms. As a result, firms facing heightened financial constraints due to capital expenditures on AI are more likely to resort to tax avoidance to generate internal funds rather than seeking external financing.

5.3 Excluding alternative channels

In Section 2, we propose that the quality of internal control could be a potential channel through which AI technology influences firms’ tax planning decisions. Prior research by Fedyk et al. (2022) and Ashraf et al. (2024) suggests that AI adoption may enhance internal control environments by improving the accuracy of financial reporting, facilitating compliance with tax laws, and optimizing operational management (Bauer, 2016), potentially leading to reduced corporate tax aggressiveness. This subsection empirically tests this hypothesis.

In line with the methodology of Gallemore and Labro (2015), we utilize three publicly observable proxies for internal control quality: (1) earnings announcement speed, defined as the number of days between the end of the fiscal year and the earnings announcement date, multiplied by negative one; (2) management forecast accuracy, measured as the absolute value of the difference between the management's last available estimate of earnings per share before fiscal year-end and the actual earnings, divided by the actual earnings, and multiplied by negative one; and (3) the absence of restatements due to unintentional errors, where the indicator variable equals zero if the firm restated the current fiscal year's financials due to errors and one otherwise. Higher values for each proxy indicate better internal control quality.

Table 11 presents the results of our analysis on the impact of AI adoption on internal control quality. The findings reveal that AI adoption significantly reduces earnings announcement speed and management forecast accuracy but does not materially affect the incidence of restatements due to errors. These results suggest that AI is not associated with an enhancement in internal control quality.

One possible explanation for this lack of improvement in internal control quality may be related to the limitations of our AI Index. This index, derived from textual analysis of firms' annual reports, may not adequately capture the specific use of AI technology in financial reporting preparation or compliance processes.

6 Conclusion

This study represents the first comprehensive examination of how increased investment in artificial intelligence influences corporate tax planning. By developing a novel measure of firm-level AI adoption, we find that a rise in AI investment correlates with increased corporate tax aggressiveness. Specifically, a one-standard-deviation increase in AI investment leads to a 0.43 percentage point increase in tax avoidance metrics. Our cross-sectional analysis further indicates that this effect is particularly pronounced among smaller firms, those in high-tech industries, and firms located in regions with lenient tax enforcement.

We also explore the mechanisms underlying the relationship between AI adoption and corporate tax aggressiveness. Our results support the hypothesis that AI investments stimulate higher R&D expenditures and innovation activities, which contribute to tax reductions for firms. Additionally, we observe that the initial high operating costs associated with AI investments create financial strain, prompting firms to engage in more aggressive tax planning to generate internal funds. Thus, both the innovation channel and the cost channel collectively explain the tax avoidance behavior associated with AI adoption.

Our findings have three significant policy implications. First, policymakers should encourage firms to leverage the dual benefits of AI investment, emphasizing its potential to drive both innovation and tax efficiency. By raising awareness and providing strategic guidance, firms can optimize their financial performance in alignment with broader policy goals of technological advancement and economic growth.

Second, since AI investments lead to increased R&D expenditures and subsequent tax reductions, there is a need to reassess existing R&D tax incentives to mitigate potential tax avoidance. Policymakers might consider imposing limits or additional criteria on tax deductions related to AI-driven R&D to ensure that these incentives foster genuine innovation without unduly impacting tax revenues.

Third, to enhance understanding and regulation of AI's impact on corporate tax planning, policymakers could mandate detailed disclosure of AI investments by firms. Improved transparency would enable tax authorities to better assess the nature and implications of AI investments for tax planning, facilitating a more balanced approach to corporate tax policy.

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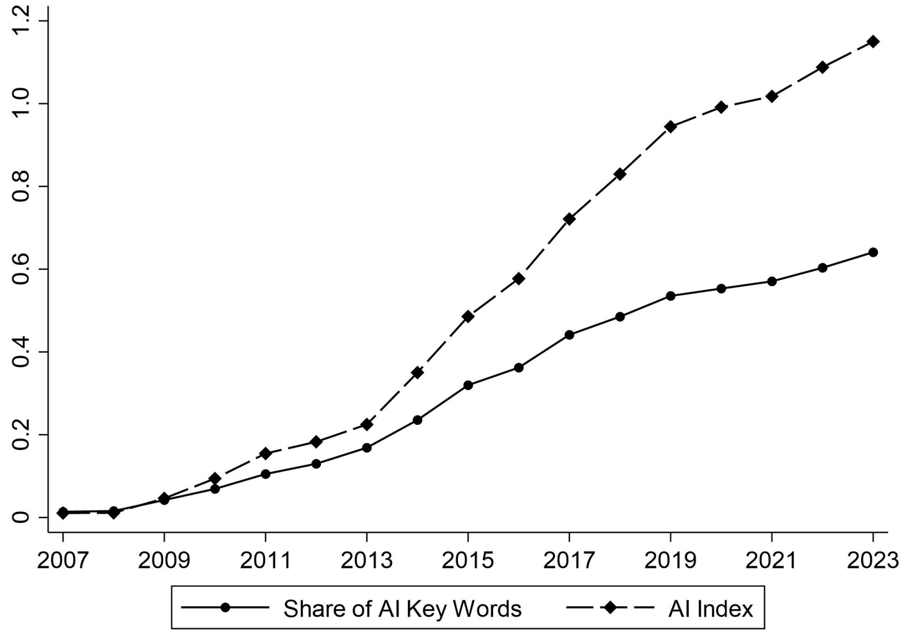
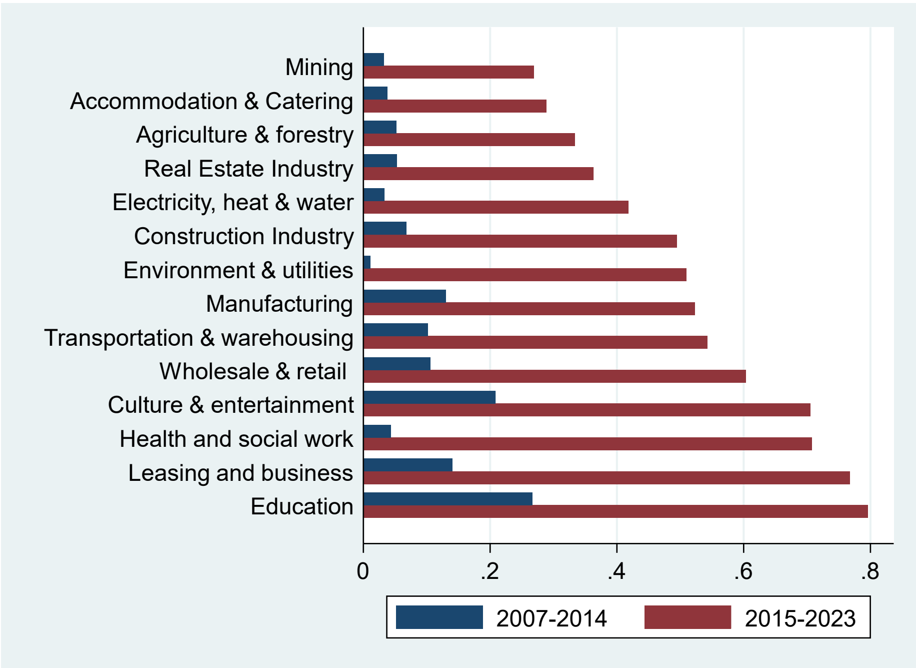
Figures and Tables



(a) Time Variation



(b) Industry Variation

Figure 1: Time and Industry Variations of AI Keywords

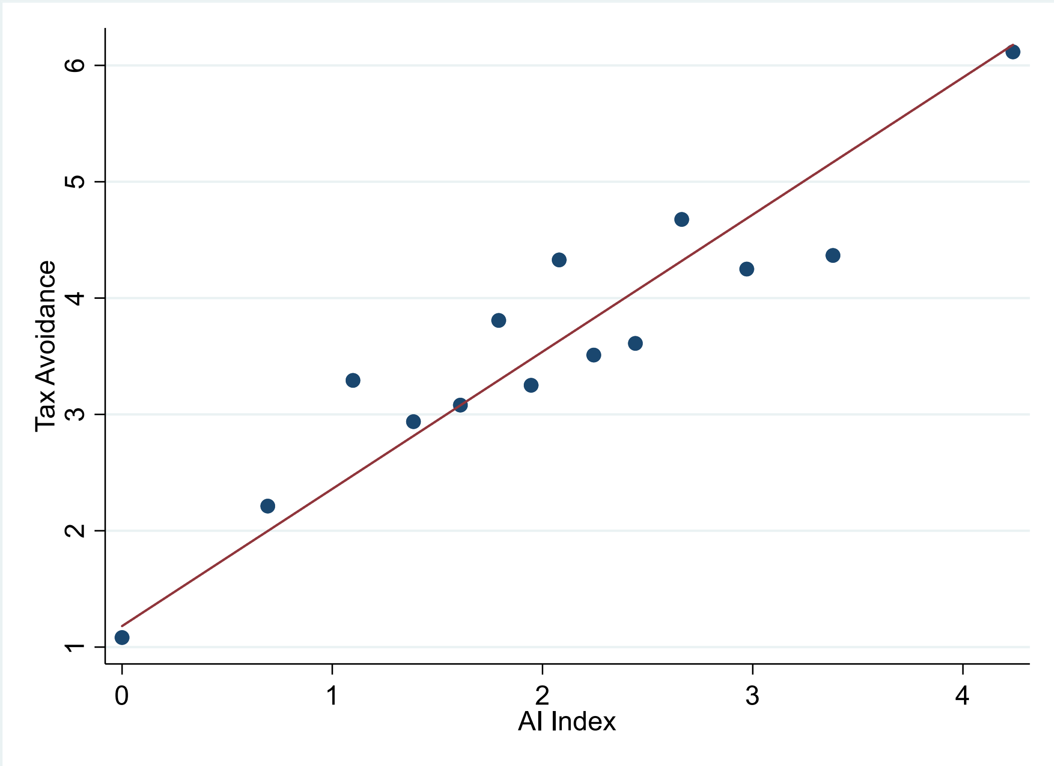


Figure 2 Relationship between AI Adoption and Corporate Tax Avoidance

Note: This figure shows the relationship between firm's adoption of AI and their tax avoidance behavior. It groups the variable AI index into equal-sized bins (number of bins = 50) and computes the mean of AI index and the DTR variables within each bin, then creates a scatterplot of these data points.

Table 1 Summary Statistics

Variables	Mean	SD	P25	Median	P75
DTR (%)	1.975	11.401	-1.758	1.559	6.368
BTD (%)	1.424	5.261	-0.743	0.837	3.3
ETR (%)	16.786	12.082	11.256	15.139	22.387
AI Index	0.674	1.043	0	0	1.099
Firm Size	8.331	1.323	7.389	8.143	9.077
Leverage	0.411	0.195	0.253	0.405	0.556
PPE	0.219	0.151	0.102	0.191	0.307
Intangibles	0.043	0.04	0.018	0.033	0.055
R&D	0.023	0.023	0.003	0.019	0.034
ROA	0.055	0.042	0.024	0.046	0.075
Cash Flow	0.056	0.068	0.017	0.054	0.095
Firm Growth	0.158	0.278	0.001	0.117	0.266
Foreign Income	0.645	0.479	0	1	1
EQINC	0.373	0.484	0	0	1

Notes: This table presents the descriptive statistics of the key variables for the full sample, including the mean and standard deviation, among many others. All variable definitions are shown in Appendix A.

Table 2 Baseline Results

VARIABLES	DTR	DTR	DTR
	(1)	(2)	(3)
AI Index	0.455***	0.458***	0.411***
	(0.121)	(0.123)	(0.123)
Size	-0.184	-0.154	-0.154
	(0.233)	(0.234)	(0.233)
Leverage	-2.396***	-1.863**	-2.372***
	(0.898)	(0.910)	(0.903)
ROA	41.915***	42.026***	41.745***
	(2.860)	(2.890)	(2.913)
PPE	2.962**	2.747**	2.588**
	(1.259)	(1.240)	(1.250)
Intangibles	11.818**	13.935***	12.424**
	(5.242)	(5.389)	(5.356)
R&D	1.902	-0.212	1.818
	(3.391)	(3.311)	(3.322)
Flow	-7.555***	-7.690***	-7.679***
	(1.235)	(1.230)	(1.230)
Growth	-0.439	-0.476*	-0.450
	(0.276)	(0.277)	(0.275)
FI	0.098	0.148	0.019
	(0.355)	(0.361)	(0.357)
EQINC	1.169***	1.170***	1.142***
	(0.184)	(0.186)	(0.185)
Constant	0.887	0.479	0.810
	(1.988)	(1.989)	(1.990)
Firm FE	Yes	Yes	Yes
Industry-year FE	Yes	No	Yes
Province-year FE	No	Yes	Yes
Observations	34,307	34,307	34,307
Adjusted R-squared	0.273	0.266	0.276

Notes: The dependent variable is *DTR*, measured as the difference between the statutory tax rate and effective tax rate. The independent variable. *AI Index* is the measure for firm's adoption of AI. See Appendix A for more details of the variable constructions. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3 Results for Instrumental Variable Approach

	(1)	(2)
	First Stage	Second Stage
VARIABLES	AI	DTR
IV	0.030***	
	(0.008)	
Instrumented AI		7.138***
		(2.234)
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry-year FE	Yes	Yes
Province-year FE	Yes	Yes
Cragg-Donald Wald F statistic	12.73	
Observations	34,307	34,307
Adjusted R-squared	0.716	-

Note: This table reports the first-stage and second-stage results of a two-stage least squares (2SLS) regression using *Port×GlobalAI* as an exogenous instrument of AI index. See Appendix A for more details of the variable constructions. Standard errors in parentheses are clustered at the firm level. One, two and three asterisks denote significance at the 10%, 5% and 1% level, respectively.

Table 4 Using Selection on Observables to Assess the Bias from Unobservables

	DTR	
	(1)	(2)
	Limited	Full
Panel A		
AI Index	0.320**	0.411***
	(0.125)	(0.123)
Controls	No	Yes
Firm FE	Yes	Yes
Industry-year FE	Yes	Yes
Province-year FE	Yes	Yes
Observations	34,307	34,307
R-squared	0.263	0.276
Panel B		
Selection Ratio ($\left\|\beta_F/(\beta_L-\beta_F)\right\|$)		4.52
Identified β -set		[0.411, 0.490]

Table 5　Results From a Propensity Score Matched Sample

VARIABLES	DTR	DTR	DTR
	(1)	(2)	(3)
AI Index	0.273**	0.321**	0.342***
	(0.131)	(0.125)	(0.121)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes
Observations	23,578	25,655	27,028
R-squared	0.324	0.316	0.314

Notes: This table reports the regression result based on the propensity score matched subsample. The dependent variable is DTR, which is measured as the difference between the statutory tax rate and the effective tax rate. Columns (1)-(3) respectively employ nearest neighbor matching algorithms with ratios of 1:3, 1:4, and 1:5. See Appendix A for more details of the variable constructions. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6 Robustness Checks: Alternative Measures for Tax Avoidance

VARIABLES	BTD	ETR
	(1)	(2)
AI Index	0.155***	-0.401***
	(0.053)	(0.120)
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry-year FE	Yes	Yes
Province-year FE	Yes	Yes
Observations	34,307	34,307
Adjusted R-squared	0.406	0.373

Notes: In column 1, the dependent variable is BTD, which is measured as the difference between pretax accounting profit and taxable income divided by firms' total assets. In column 2, the dependent variable is ETR, which is measured by the effective tax rate. See Appendix A for more details of the variable constructions. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7 Robustness Checks：Alternative Definitions of AI Adoption

VARIABLES	DTR	DTR
	(1)	(2)
High Adoption of AI × *Post*	0.536***	
	(0.189)	
AI Index (MD&A) × *Post*		0.400***
		(0.124)
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry-year FE	Yes	Yes
Province-year FE	Yes	Yes
Observations	34,307	33,805
Adjusted R-squared	0.276	0.275

Notes: The dependent variable is DTR, which is measured as the difference between the statutory tax rate and effective tax rate. *High Adoption of AI* is an indicator variable that equals one if the firm's AI index is greater than zero, and zero otherwise. *AI Index (MD&A)* is the natural logarithm of one plus the count of AI-related keywords present in the *MD&A* of the firms' annual reports. See Appendix A for more details of the variable constructions. Standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8 Heterogeneous Impacts

	Panel A: Firm Size		Panel B: High Tech Industry		Panel C: Tax Enforcement	
	Large	Small	Yes	No	High	Low
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
AI Index	0.216	0.540***	0.066	0.454***	0.023	0.584***
	(0.159)	(0.190)	(0.244)	(0.133)	(0.181)	(0.158)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,524	16,763	4,476	29,690	11,827	22,451
R-squared	0.308	0.252	0.356	0.275	0.284	0.276
P-value	0.017		0.023		0.002	

Notes: The dependent variable is DTR, which is measured as the difference between the statutory tax rate and effective tax rate. In Panel A, a firm is included in the large (small) size group if its value of assets is above (below) the sample median at the end of 2023. In Panel B, we divide the full sample into two subsamples, namely, a high-tech subsample and a non-high-tech subsample. In Panel C, we measure the strictness of tax enforcement by using the legal environmental index developed by Fan et al. (2011). A firm is included in the strict (lax) enforcement group if the region has a legal environmental index above (below) the sample median at the end of 2023. All standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, using a one-tailed test when a prediction is indicated.

Table 9 Mechanism Tests: the Innovation Channel

VARIABLES	R&D (1)	Patent Applied (2)	Patent Granted (3)	Innovation Quality (4)	Innovation Efficiency (5)
AI Index	0.001***	0.042***	0.063***	0.111***	0.041**
	(0.0002)	(0.013)	(0.012)	(0.013)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes
Observations	34,307	33,370	33,370	22,469	27,698
Adjusted R-squared	0.745	0.709	0.663	0.802	0.640

Notes: This table investigates how firms' adoption of AI affects its innovation activities. In column 1, the dependent variable is *R&D*, which is the ratio of R&D expenditure divided by lagged assets. In column 2, the dependent variable is *Patent Applied*, which is the natural logarithm of one plus the number of patents applied. In column 3, the dependent variable is *Patent Granted*, which is the natural logarithm of one plus the number of patents granted. In column 4, the dependent variable is *Innovation Quality*, which is the natural logarithm of one plus the number of patent cited. In column 5, the dependent variable is *Innovation Efficiency*, which is calculated by using *Patent Granted* divided by R&D expenditure. All standard errors in parentheses are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10 Mechanism Tests: the Operating Cost Channel

VARIABLES	COGS (1)	Profit Margin (2)	Financial Constraint (3)	TFP (4)
AI Index	0.004***	-0.004***	0.109***	0.016***
	(0.001)	(0.001)	(0.016)	(0.006)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Observations	34,254	34,307	29,636	29,882
Adjusted R-squared	0.860	0.640	0.799	0.936

Notes: This table estimates how AI adoption affects firms' operating cost and productivity. In column 1, the dependent variable is COGS, measured by the cost of goods sold divided by sales. In column 2, the dependent variable is net profit margin, which is ratio of net profit to sales. In column 3, the dependent variable is financial constraint, which is proxied by KZ index (Kaplan and Zingales, 1997). Larger values of the index indicate a greater level of financial constraint. In column 4, the dependent variable is revenue TFP, calculated following Levinsohn and Petrin (2003).

Table 11 Mechanism Tests: Internal Control Quality

VARIABLES	Earning Announcement Speed (1)	Management Forecast Accuracy (2)	Absence of Restatement (3)
AI Index	-0.007***	-0.014*	-0.004
	(0.002)	(0.008)	(0.004)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes
Observations	33,980	15,095	34,307
Adjusted R-squared	0.430	0.268	0.366

Notes: This table estimates how AI adoption affects firms' internal control quality. In column 1, the dependent variable is earning announcement speed, measured as the natural logarithm of number of days between the end of the fiscal year and the earnings announcement date, multiplied by negative one. In column 2, the dependent variable is management forecast accuracy, measured as the absolute value of management's last available estimate of earnings before fiscal year-end minus the firm's actual earnings, divided by the firm's actual earnings at the end of the year and multiplied by negative one. In column 3, the dependent variable is absence of restatement, which is an indicator variable equal to zero if the firm restated the current fiscal year due to error, and one otherwise.

Appendix A: Example on AI-related Description in Annual Report

Table A1: AI-related Information Disclosed in the Annual Report

Firm Name	**Year**	**Industry**	**AI-related information disclosed in annual report**
Zhonggong Education (002607.SZ)	2023	Education	In 2023, the company seized new opportunities brought by the wave of emerging technologies and established the **Artificial Intelligence** and Education Research Institute. The company selected public service employment training as the first vertical application scenario to explore a new paradigm of "**AI** + Content" production. By deeply analyzing learners' data and needs, the company restructured training and teaching content. Additionally, leveraging AI technologies to enhance teaching efficiency and the intelligence of learning tools, the company has broken through the bottlenecks of traditional training models.
Mason Technologies (002654.SZ)	2023	Leasing and business services	The company has high brand recognition in fields such as 3C electronic display indicators, TV backlighting, **smart home**, fire safety and security, rail transit lighting, and advertising signage lighting. It is positioned in the top tier of the industry. The company primarily serves clients such as publicly listed companies or their subsidiaries, large enterprise groups, brand-name companies, and leading clients in specialized and innovative industries.
Tsinghua Tongfang (600100.SH)	2020	Manufacturing	Building on the existing product system, the company integrates new technologies such as **artificial intelligence, knowledge graph, and machine learning** to continuously enrich and improve the Tongfang big data product system and enhance analytical service capabilities.
Hikvision Digital (002415.SZ)	2018	Manufacturing	In 2018, Hikvision leveraged its solid technical expertise in image capture and AI algorithms to enhance its "Mingmou" series of near-range **facial recognition** products. The new products feature faster **facial recognition** response times, more user-friendly **human-computer interaction**, and support for larger-scale facial comparison and liveness detection. This significantly expands the application scenarios of **facial recognition** technology across various edge applications such as access control, attendance, consumption, visitor management, and elevator control.

Appendix B: Details on the Construction of AI Index

We construct the AI Index following the procedures below.

First, we download the annual reports for all listed-firm in China from 2007-2023 and extract their text data.

Second, we use machine learning method to obtain 73 AI-related keywords. Based on research reports and the artificial intelligence lexicon provided by the World Intellectual Property Organization, 52 terms were manually selected as seed words. Using Word2vec technology and the Skip-gram model, the terms from annual reports were used as the corpus for training. According to the cosine similarity between the seed words and the output words, the top 10 words closest in semantic meaning to each seed word were selected. Then, duplicate words, words irrelevant to artificial intelligence, and words with too low frequency were removed. In the end, a total of 73 terms were obtained to form the artificial intelligence lexicon used in this paper. See Table B1 for the list of AI-related keywords.

Third, we calculate the number of AI-related keywords in each firm's annual report for each year.

Finally, the AI index is calculated as AI Index = *Ln*(1+ *Keyword*), where *keyword* is the number of AI-related keywords.

Table B1: List of AI-related Keywords

Artificial Intelligence	AI product	AI chip	Machine Translation	Machine Learning
Computer Vision	Human-Computer Interaction	Deep Learning	Neural Network	Biometrics
Image Recognition	Data Mining	Feature Recognition	Speech Synthesis	Speech Recognition
Knowledge Graph	Smart Banking	Smart Insurance	Human-Machine Collaboration	Smart Regulation
Smart Education	Intelligent Customer Service	Smart Retail	Smart Agriculture	Robo-Advisor
Augmented Reality	Virtual Reality	Smart Healthcare	Smart Speaker	Intelligent Voice
Smart Governance	Autonomous Driving	Smart Transportation	Convolutional Neural Network (CNN)	Voiceprint Recognition
Feature Extraction	Driverless Driving	Smart Home	Question-Answering System	Facial Recognition
Business Intelligence	Smart Finance	Recurrent Neural Network (RNN)	Reinforcement Learning	Intelligent Agent
Smart Elderly Care	Big Data Marketing	Big Data Risk Control	Big Data Analytics	Big Data Processing
Support Vector Machine (SVM)	Long Short-Term Memory (LSTM)	Robotic Process Automation (RPA)	Natural Language Processing (NLP)	Distributed Computing
Knowledge Representation	Smart Chip	Wearable Devices	Big Data Management	Smart Sensors
Smart Sensors	Edge Computing	Big Data Platform	Smart Computing	Smart Search
Internet of Things (IoT)	Cloud Computing	Augmented Intelligence	Voice Interaction	Smart Environmental Protection
Human-Machine Dialogue	Deep Neural Network (DNN)	Big Data Operations		

Appendix C: Description and definition of key variables

DTR = the difference between statutory and effective tax rates.

BTD = the ratio of the difference between pretax book income and taxable income to firms' total assets.

ETR = ratio of income tax expenses to pretax accounting profit.

Labor Intensity = natural logarithm of the ratio of the number of employees to fixed assets.

Size = logarithm of firm's total asset.

Lev = total liabilities divided by total assets.

ROA = ratio of net profits over total assets.

PPE = fixed assets divided by total assets

Intangibility = intangible asset divided by total assets

R&D = research and development expenses divided by lagged total assets

Flow = operating cash flow divided by total assets

Growth = growth rate of sales revenue

FI = equals one if the firm generates foreign income, and zero otherwise.

EQINC = equals one if the firm has equity income received from unconsolidated entities, and zero otherwise.

Patent Applied = natural logarithm of one plus the number of patents applied.

Patent Granted = natural logarithm of one plus the number of patents granted.

Innovation Quality = natural logarithm of one plus the number of patent cited.

Innovation Efficiency = natural logarithm of the ratio of one plus the number of patents granted to R&D expenditure.

COGS = the cost of goods sold divided by sales.

Net Profit Margin = ratio of net profit to sales.

Financial Constraint = KZ index proposed by Kaplan and Zingales (1997).

Earning Announcement Speed = natural logarithm of number of days between the end of the fiscal year and the earnings announcement date, multiplied by negative one.

Management Forecast Accuracy = absolute value of management's last available estimate of earnings before fiscal year-end minus the firm's actual earnings, divided by the firm's actual earnings at the end of the year and multiplied by negative one.

Absence of Restatement = an indicator variable equal to zero if the firm restated the current fiscal year due to error, and one otherwise.

Appendix D: Additional figures for PSM-DID

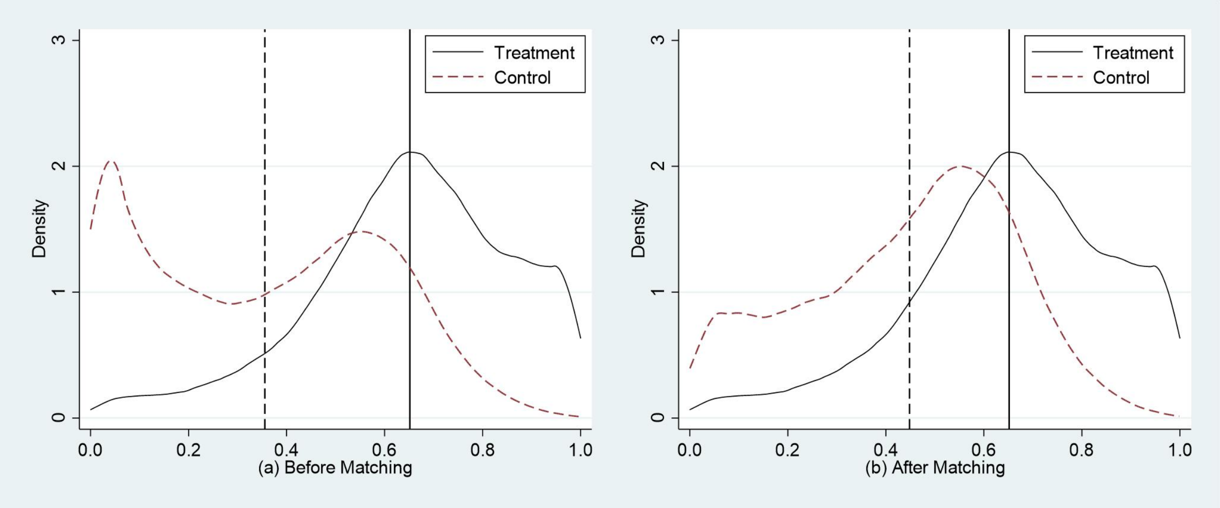


Figure D1 Propensity Score Distribution before and after Matching

Note: In the left-hand figure, we present the propensity score distribution before matching, while the right-hand figure shows the distribution after matching. In both figures, the horizontal axis depicts the propensity scores, and the vertical axis represents the kernel density. The solid vertical line indicates the mean distribution value for the treatment group, whereas the dashed vertical line denotes the mean for the control group.

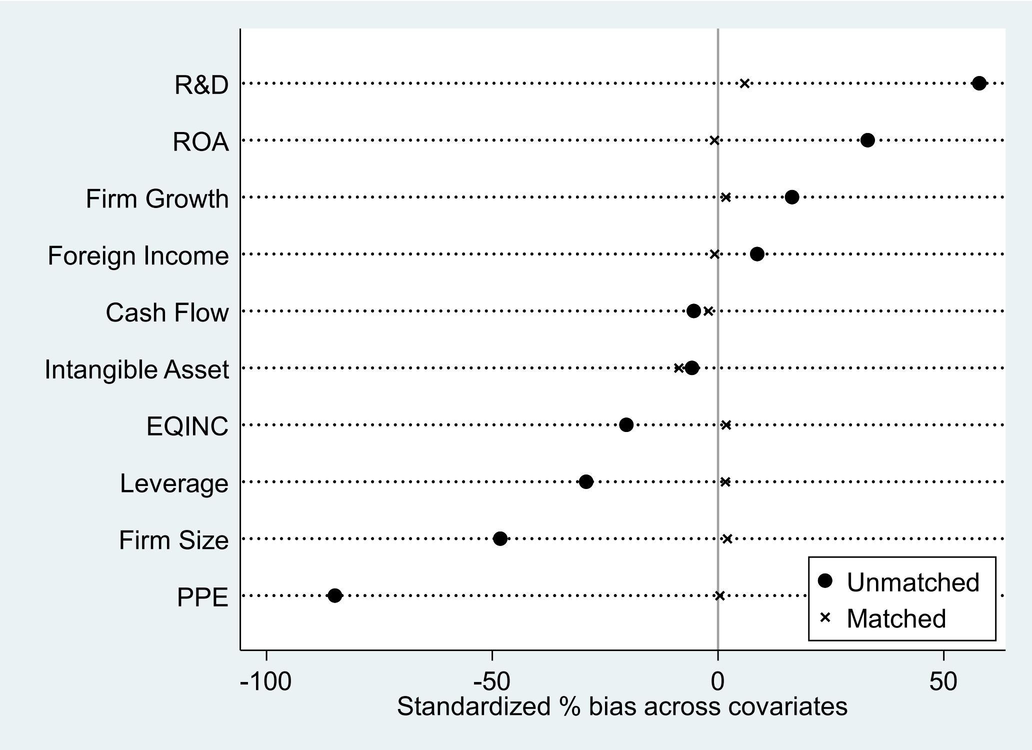


Figure D2 Comparison of Covariate Differences before and after Matching