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How Does Artificial Intelligence Reshape Bank Profitability in China?—Evidence from a Multi-Period Difference-in-Differences Model

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Abstract

Artificial intelligence (AI) has become an integral driver of digital transformation in the banking sector, fundamentally influencing operational efficiency, resource allocation, and profitability. This study investigates how AI adoption affects the profitability of Chinese commercial banks and through which mechanisms these effects occur, within the context of the country's broader financial digitalization process. Using panel data for 17 A-share listed banks in China from 2009 to 2022, we employ a multi-period difference-in-differences (DID) framework—whose validity rests on the parallel trend assumption, empirically verified through an event-study specification—and combine it with propensity score matching (PSM) and placebo simulations to ensure credible causal identification. The results indicate that AI adoption significantly improves bank profitability. Mechanism analyses suggest that AI enhances profitability through two overarching channels—operational efficiency and resource allocation—manifested in (i) higher cost elasticity of income, (ii) improved deposit–loan turnover adaptability via more efficient liquidity and funding-cycle management, and (iii) optimized cross-business capital allocation efficiency through better risk–return matching in diversified operations. The effects are stronger for banks with higher digital investment intensity and tighter customer stickiness–liability cost coupling, and vary systematically across ownership types, bank sizes, and policy cycles. Overall, the findings provide policy-relevant evidence on how AI-driven digital transformation can enhance bank performance and risk management in modern financial systems. This study contributes by constructing a disclosure-based AI adoption measure from bank annual reports and exploiting staggered adoption with a multi-period DID design to provide causal evidence from China's listed banking sector.

Keywords: artificial intelligence; digital transformation; financial services; resource allocation; deposit–loan turnover adaptability; multi-business capital allocation efficiency; customer stickiness–liability cost coupling



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1. Introduction

AI, as a disruptive technological innovation, has profoundly reshaped the structure and dynamics of modern production systems. In accordance with Schumpeter's theory of innovation (Aghion & Howitt, 1992), AI reconstructs and recombines production factors, driving paradigm shifts in technology and substantially strengthening total factor productivity (TFP). Consistent with the theory of technology diffusion (Griliches, 1957), the

penetration of AI across various industries accelerates knowledge spillovers and innovation iteration, facilitating the upgrading of industrial value chains toward higher value-added segments. Moreover, following the technology life cycle theory (Santos et al., 2025), the evolution of AI—from its introduction to maturity—continues to generate new products, services, and business models, injecting persistent dynamism into the technological innovation system.

At the same time, the banking industry is encountering increasingly complex and multifaceted competitive and operational challenges (Roy et al., 2025). On one hand, the ongoing liberalization of interest rates (Kang et al., 2024) and the deepening trend of financial disintermediation (Agarwal & Baron, 2024) have steadily narrowed the traditional interest margin derived from deposit–loan spreads. On the other hand, fintech firms, leveraging technological superiority, have captured substantial market shares in areas such as payment settlement and consumer finance, further eroding the profitability boundaries of traditional banks (Deng et al., 2022). Against this backdrop, AI technologies present a new strategic pathway for banks to overcome conventional operational bottlenecks (Gyau et al., 2024). Industry evidence indicates that early adopters of AI have begun to exhibit notable improvements in profitability (Fraisie & Laporte, 2022; Gyau et al., 2024; Liu et al., 2025). Consequently, systematically exploring the mechanisms through which AI affects bank profitability is of significant practical relevance, enabling banks to better seize technological opportunities and optimize their profit models (Durongkadej et al., 2024).

Research on the relationship between AI and bank profitability remains at a nascent stage. A keyword frequency index was constructed to measure AI-related terms, providing a foundational quantitative tool for assessing technological adoption (Wu et al., 2023). The association between fintech investment and bank performance was empirically verified, but the specific transmission channels through which AI influences profitability were not disentangled (Tian & Ge, 2023). The management expense ratio was adopted as a proxy for digitalization input, yet the dynamic interactive effects among relevant variables were overlooked (Pan & Zhang, 2023).

Nevertheless, three major gaps remain in the literature on AI-enabled digital transformation in banking and financial services. First, existing studies often document associations between technology adoption and performance without systematically unpacking the mechanism chain through which AI translates into profitability gains—particularly via operational efficiency improvements and resource allocation upgrades (including risk management and risk–return matching). Second, causal identification is frequently constrained by endogeneity; evidence based on quasi-natural experiments and time-varying AI adoption remains limited. Third, the empirical coverage is uneven across institutional settings, and relatively little is known about how the profitability effects of AI differ across bank characteristics (e.g., ownership, size, and digital investment intensity) and policy cycles in emerging markets such as China.

Building upon the identified research gaps, this study aims to advance the understanding of how AI reshapes the profitability structure of Chinese commercial banks. While prior studies have documented the general association between fintech and bank performance, most have remained descriptive, lacking robust causal identification and clear theoretical mechanisms linking AI adoption to profitability. Moreover, the institutional uniqueness of China’s banking sector—characterized by strong government participation, heterogeneous ownership structures, and uneven levels of digital maturity—renders international evidence insufficient for explaining local dynamics. Against this backdrop, this research responds to both theoretical and empirical needs by providing new causal evidence and mechanism-based insights into AI’s economic value within banking.

To bridge these gaps, this study contributes in three key aspects: 1. It provides causal evidence on the profitability impact of AI adoption in banking by combining a multi-period DID framework with PSM and extensive robustness checks, based on a panel of 17 Chinese A-share listed banks over 2009–2022. 2. It develops an efficiency-and-allocation mechanism perspective by showing how AI boosts profitability through operational efficiency (cost elasticity of income) and resource allocation (deposit–loan turnover adaptability and multi-business capital allocation efficiency), highlighting the role of AI in upgrading risk management and risk–return matching. 3. It documents systematic heterogeneity across ownership types, bank sizes, digital investment intensity, and customer stickiness–liability cost coupling, and discusses implications for AI-driven digital transformation policies in financial services.

2. Theoretical Framework and Research Hypotheses

2.1. Effects of Artificial Intelligence on Bank Profitability

AI has become a key driver of transformation in banking, fundamentally altering business operations, risk management, and profitability structures. Existing international studies generally find that AI adoption enhances banks' efficiency and performance by automating credit assessment, improving risk prediction, and streamlining compliance tasks (Hughes et al., 2022; Sheth et al., 2022; Fraisse & Laporte, 2022). These findings align with the Schumpeterian view that technological innovation reorganizes production factors and enhances productivity (Aghion & Howitt, 1992). However, most existing research treats AI as a homogeneous technological shock, focusing on correlation rather than causation, and offering limited insight into the mechanisms through which AI transforms financial performance.

In China, where commercial banks operate under a hybrid system of market competition and policy influence, evidence remains fragmented. Prior studies (Tian & Ge, 2023; Pan & Zhang, 2023) confirm that fintech and AI investment correlate with higher profitability and cost efficiency, yet lack dynamic causal identification and mechanism testing. Moreover, heterogeneity in ownership and governance structures further complicates the analysis. Consequently, the mechanisms through which AI enhances profitability—whether by improving operational efficiency or optimizing resource allocation—remain underexplored, motivating this study's focus on causal inference and mechanism-based analysis. Importantly, China's banking system provides an ideal setting for examining the interaction between technology adoption and institutional design. It is not only the world's largest banking sector by asset size but also a system where policy-driven innovation, state ownership, and market competition coexist, creating a unique “semi-marketized laboratory” for testing theories of digital transformation and financial innovation. The rapid pace of AI deployment—accelerated by national strategies such as “Smart Finance” and “Digital China”—offers a natural quasi-experimental environment to observe how technological adoption reshapes profitability under different governance regimes.

Amid the rapid evolution of financial technology, AI has become integral to core banking operations owing to its superior algorithmic and data-processing capabilities. By mitigating information asymmetry between borrowers and lenders, AI reduces adverse selection and moral hazard, thereby improving credit risk pricing and decision accuracy (Hughes et al., 2022). Through automation and intelligent analytics, banks can transform accumulated data assets into competitive advantages, enhancing both efficiency and risk control. Transaction cost theory further explains that “search, negotiation, and supervision costs” represent key sources of inefficiency, while AI-driven automation effectively replaces manual due diligence and contract screening, reducing time costs and human error (Sachan et al., 2024).

In addition, AI facilitates more efficient resource allocation across business units, enabling a dynamic balance between risk and return. The efficiency gains, however, depend on the intensity of digital investment—once investment surpasses a threshold, AI integration generates exponential improvements in decision precision and operational coordination (Shrestha et al., 2021). Meanwhile, the coupling between customer stickiness and liability cost ensures stable, low-cost funding, creating favorable conditions for profitability transformation and sustainable competitive advantage (Ekinci et al., 2014).

H1. *Artificial intelligence significantly enhances bank profitability.*

2.2. Mechanism Pathways

To align with the AI-driven digital transformation perspective in financial services, we conceptualize the profitability effect of AI as operating through two overarching channels: operational efficiency and resource allocation. Operational efficiency is reflected in the bank's ability to convert costs into revenues more effectively (cost elasticity of income). Resource allocation is reflected in both the efficiency of the funding cycle (deposit–loan turnover adaptability) and the quality of risk–return matching across diversified business lines (multi-business capital allocation efficiency). Accordingly, we propose three mechanism hypotheses to explain how AI adoption translates into higher bank profitability.

2.2.1. Cost Elasticity of Income

Bank profitability fundamentally depends on the dynamic balance between “revenue expansion” and “cost control.” The cost elasticity of income—measuring the sensitivity of income growth to cost fluctuations—serves as a key intermediary mechanism. A higher coefficient indicates that income growth can better buffer cost increases, thereby improving profitability stability and growth potential (Lepetit et al., 2008).

Based on economies of scale theory, when income grows faster than costs, the marginal revenue effect expands profit margins. Cost stickiness theory further suggests that operational costs are often rigid during contraction periods, but higher elasticity allows rapid income growth to offset these rigid costs, preventing profit erosion.

AI-driven cost management transforms accounting from “passive recording” to “proactive optimization.” For instance, robotic process automation (RPA) can automate repetitive tasks such as expense reimbursement and vendor reconciliation, while natural language processing (NLP) analyzes contract clauses to identify cost-optimization opportunities (Kokina & Blanchette, 2019). Simultaneously, AI systems can push customized structured deposit products to wealth-management clients and preferential loan packages to credit-demand customers, thereby boosting operating income (Sheth et al., 2022).

Hence, improving cost elasticity of income means optimizing how efficiently costs convert into revenues. This directly strengthens profitability.

H2. *AI improves bank profitability by augmenting cost elasticity of income.*

2.2.2. Deposit–Loan Turnover Adaptability

Bank profitability rests on efficient value transformation across the entire fund cycle: absorption, allocation, and circulation (Acharya & Mora, 2015). Banks gather funds through deposits and interbank borrowing, essentially purchasing the right to use capital at lower costs. They then deploy these funds through loans, bond investments, or wealth products to generate returns. Quick repayment and reinvestment cycles speed up capital turnover and reduce liquidity drag (Koroma & Bein, 2024).

AI elevates deposit–loan turnover by forecasting fund supply and demand more accurately. Long short-term memory (LSTM) models integrate deposit fluctuations, loan

applications, and economic indicators to predict liquidity gaps by region and timeframe (H. Jiang et al., 2021). Before mortgage application surges, banks can launch intelligent deposit products to secure stable long-term funding (DeAngelo & Stulz, 2015). Meanwhile, NLP and graph neural networks (GNN) analyze industry reports and policy documents to identify promising lending and investment opportunities with favorable risk-return profiles (Ashrafzadeh et al., 2025), supporting steady growth in fund turnover efficiency (Guo & Zhang, 2023).

H3. *AI enhances bank profitability by improving deposit–loan turnover efficiency.*

2.2.3. Multi-Business Capital Allocation Efficiency

According to the financial symbiosis theory, profitability in diversified banking operations depends on the efficiency of “risk–return” mismatches across business lines. Since business units differ in capital duration, risk exposure, and return elasticity, dynamically matching funds—allocating long-term funds to stable, low-risk projects and short-term funds to high-turnover activities—reduces idle capital and enhances overall return, reinforcing both scale and structural resilience.

The efficiency of such multi-business capital allocation reflects both internal and cross-line fund adaptation. AI, through reinforcement learning, integrates inflow and outflow data (e.g., customer redemptions and project financing schedules), risk parameters (e.g., non-performing loan (NPL) ratios, which measure credit default risk, and net asset value (NAV) volatility, which captures portfolio value fluctuations), and return curves (e.g., underwriting fees and management commissions) to construct multimodal temporal models. These models dynamically track capital utilization efficiency and risk exposure while simultaneously calculating the value-at-risk (VaR) across diversified business portfolios (Nyqvist et al., 2024).

H4. *AI improves bank profitability by strengthening multi-business capital allocation efficiency.*

2.2.4. Digital Investment Intensity

The transformation efficiency from technology to profit relies on the dynamic moderation of digital investment intensity. Moving beyond the linear assumption of “more investment yields better performance,” this mechanism aligns investment with business compatibility, synergy, and profit-conversion cycles. From a resource allocation perspective, digital investment represents a sunk cost (Åstebro, 2004), and its impact on profitability exhibits a “threshold effect.” Insufficient investment fails to cover core business scenarios, whereas excessive investment causes technological redundancy, escalating costs and extending conversion cycles.

AI enables precise calibration of investment intensity through real-time technology–business feedback. Reinforcement learning algorithms optimize resource allocation by dynamically adjusting investment scales across different operational scenarios, while natural language processing (NLP) and long short-term memory (LSTM) models monitor coordination logs and transaction cycles to fine-tune investment timing. At the same time, ROI (Return on Investment)–based feedback mechanisms—where ROI represents the ratio of net gains to invested capital—provide real-time performance evaluation, triggering automatic stop-loss adjustments and reallocating resources toward higher-yield applications (Ghosh et al., 2025).

H5. *Digital investment intensity positively moderates the relationship between AI and bank profitability—the higher the investment intensity, the stronger the profitability enhancement effect of AI.*

2.2.5. Customer Stickiness–Liability Cost Coupling

From the liability perspective and financial intermediation theory, a bank's core advantage lies in securing "stable, low-cost funding." High coupling between customer stickiness and liability costs amplifies profitability through cost–benefit dynamics: loyal customers tend to choose long-term, low-interest deposits, lowering acquisition and retention costs (Wen & Liang, 2025). In contrast, weak coupling forces banks to offer higher interest rates to attract deposits, thereby compressing margins.

AI strengthens this coupling through bidirectional learning. By constructing customer lifetime value (CLV) models based on deep learning and customer segmentation theory, AI integrates transaction and interaction data to identify high-loyalty clients. It then tailors personalized, step-rate long-term deposit products that enhance customer retention and secure low-cost, stable funding (Ekinci et al., 2014).

H6. *Customer stickiness–liability cost coupling mediates the positive effect of AI on bank profitability.*

3. Research Design

3.1. Sample Selection and Data Sources

This study selects all A-share listed commercial banks in China from 2009 to 2022 as the research sample. The financial and operational data were obtained from the Wind and CSMAR databases, which provide comprehensive and authoritative coverage of the Chinese financial sector.

This study follows recent empirical literature that identifies AI adoption through text-based methods applied to corporate disclosures and reports. For instance, previous studies construct a machine-learning-based AI dictionary from firms' annual reports and patents, finding that AI adoption significantly enhances productivity (Yao et al., 2024). Other research employs text-mining approaches to measure FinTech intensity and confirms the profitability effects of AI and big data in the banking sector (Zhang, 2022). Extending this logic, further studies use text-based identification of AI and digital transformation to examine innovation and productivity outcomes (Gan et al., 2023; S. Tang et al., 2020). Together, these studies demonstrate that textual analysis provides a valid and replicable approach for measuring AI adoption at the firm level.

In our setting, Chinese listed banks are subject to uniform disclosure regulations and external audits, ensuring that AI-related textual disclosures represent substantive technological deployment rather than symbolic statements. Furthermore, multiple robustness checks are conducted to confirm the consistency of results and to rule out spurious correlations. Hence, the empirical design of this study adheres to best practices in contemporary empirical finance and organizational economics, offering a rigorous and credible causal identification of AI's impact on bank profitability.

When merging banking and AI data, we adjusted for timing differences between quarterly and annual reporting. Data from the first two quarters of each year were matched to the previous fiscal year's AI indicators. Data from the last two quarters were matched to the current year's AI variables. This approach prevents misalignment between when events occur and how they are reported annually.

For missing data points, we consulted official quarterly reports and other bank disclosures. When reliable information was unavailable, we used linear interpolation and mean imputation to maintain panel continuity.

After cleaning and merging, we built a balanced panel dataset covering 17 listed banks across multiple quarters. This "bank-quarter" panel provides a solid foundation for the empirical analysis. Although the sample size is relatively limited, it captures the full population of listed banks in China, representing more than 80% of total banking assets and

covering the dominant entities in both state-owned and joint-stock categories. The panel's broad temporal coverage (2009–2022) and the application of multi-period DID estimation combined with robustness checks and placebo simulations ensure sufficient statistical power and reliability of inference. Therefore, the dataset provides both representative coverage and credible identification, forming a solid empirical foundation for analyzing the impact of AI adoption on bank profitability.

3.2. Variable Definitions

3.2.1. Dependent Variable

Return on Assets (ROA) is a classical indicator widely used to assess a bank's profitability, reflecting the institution's ability to generate net income from its total asset base (Zhang, 2022). Accordingly, this study employs ROA as the dependent variable, serving as the primary measure of listed banks' profitability performance.

To ensure robustness and consistency of the empirical results, the analysis further incorporates Return on Equity (ROE) as an alternative proxy in the robustness checks, thereby validating the stability of the findings from multiple profitability perspectives.

3.2.2. Core Explanatory Variable

From 2009 to 2022, AI in banking evolved from simple automation to integrated intelligent systems. Early use focused on data mining and optical recognition to streamline operations. After 2014, machine learning and natural language processing (NLP) enabled intelligent risk control and customer service. Since 2019, deep learning and robotic process automation (RPA) have become mainstream. In China, national digital strategies accelerated this shift, making AI a core driver of efficiency and innovation. The key explanatory variable in this study is the interaction term $AI \times Post$, which captures the dynamic effect of AI adoption on bank profitability. The variable AI is defined as a binary indicator that equals 1 if a bank has substantively adopted AI technologies in a given year, and 0 otherwise. Following prior studies (Yu et al., 2025), we identify AI adoption through textual analysis of annual reports and financial disclosures. Specifically, if AI-related keywords—such as “artificial intelligence,” “intelligent risk control,” “machine learning,” “deep learning,” or “intelligent customer service”—appear in a bank's official disclosures during year t , the AI variable for that bank-year observation is set to 1, indicating that the bank has initiated AI-related business activities. If no such keywords are found, $AI = 0$.

The identification of AI adoption is based on a comprehensive keyword dictionary containing 72 core and extended AI-related terms, covering technological, application, and infrastructure dimensions. These include keywords related to AI technologies (e.g., deep learning, neural networks, computer vision), financial applications (e.g., intelligent risk control, smart finance), and supporting infrastructures (e.g., big data platform, cloud computing). This multi-dimensional keyword set ensures a more accurate and systematic identification of substantive AI adoption rather than superficial mentions. Due to the large number of AI-related disclosure keywords identified from the annual reports, the complete list is provided in Appendix A.

The variable $Post$ serves as a time indicator, taking the value of 1 for all periods following the first recorded year of AI adoption by a bank, and 0 for all preceding years. The interaction term $AI \times Post$ thus isolates the incremental impact of AI implementation on profitability beyond pre-existing differences between adopting and non-adopting banks. Conceptually, this specification captures how the transition from “non-adoption” to “active AI engagement” alters banks' operational efficiency and performance trajectories over time.

3.2.3. Control Variables

Bank-specific factors, including capital adequacy, capital strength, net interest margin (NIM), and total asset size, are controlled for in the model (S. F. Tang & Wu, 2024). These variables capture key structural and operational characteristics, with detailed measurements presented in the descriptive statistics section. In addition, the broader macroeconomic environment is accounted for using three indicators: GDP growth, M2 growth, and the Banking Prosperity Index. GDP growth reflects overall economic conditions, M2 growth represents the broad money supply that indicates market liquidity, and the Banking Prosperity Index—compiled by the China Banking Association—captures the overall business climate and sentiment within the banking sector.

3.2.4. Mechanism Variable

Cost Elasticity of Income

Cost elasticity of income is measured as the ratio of operating income growth to the change in the cost-to-income ratio, adjusted by the share of administrative expenses (Abbas et al., 2024). We use arc elasticity rather than point elasticity for this calculation. While point elasticity reflects only instantaneous effects, arc elasticity captures the average responsiveness of costs to income changes over the full year. This approach minimizes bias.

AI enhances this elasticity through intelligent pricing and dynamic cost-control models. By optimizing the link between costs and revenue, these technologies ultimately boost operational efficiency (Ban & Keskin, 2021).

Deposit–Loan Turnover Adaptability

Deposit–loan turnover adaptability is defined as the deposit–loan scale matching ratio multiplied by asset profitability efficiency, divided by the year-on-year growth rate of M2 (Koroma & Bein, 2024). Asset profitability efficiency is measured as net profit divided by total assets for the year, reflecting a bank's ability to generate profit from its asset base and the efficiency with which capital turnover is transformed into profitability. This composite indicator captures the balance between a bank's funding absorption capacity and fund utilization efficiency.

AI applications in fund forecasting and allocation—through big data analytics and predictive algorithms—enable banks to anticipate liquidity needs and optimize deposit–loan alignment. This process enhances capital flow efficiency, establishing a transmission channel through which AI strengthens profitability (Bai et al., 2023).

Multi-Business Capital Allocation Efficiency

Multi-business capital allocation efficiency is measured as $(1 - \text{Total Loans}/\text{Total Assets}) \times (\text{Total Deposits}/\text{Total Liabilities})$. The first component, $(1 - \text{Total Loans}/\text{Total Assets})$, inversely represents asset diversification: a lower loan ratio indicates reduced dependence on single credit operations and higher business diversification. The second component, $(\text{Total Deposits}/\text{Total Liabilities})$, reflects funding stability, as a higher deposit ratio corresponds to lower funding costs and liquidity risks. Together, these indicators capture a bank's ability to allocate funds dynamically across diversified operations, thus improving profitability resilience.

3.2.5. Moderating Variables

Digital Investment Intensity

Digital investment intensity is measured as administrative expenses divided by total assets. The integration of digital investment with AI technology may either amplify or mitigate AI's influence on bank profitability. Digital investment intensity is introduced as a

moderating variable to examine how it affects both the direction and magnitude of AI's impact on profitability (Tian & Ge, 2023).

Due to data availability constraints, the management expense ratio (management expenses/total assets) is used as a proxy variable for digital investment intensity (Pan & Zhang, 2023). This choice is based on the fact that banks typically record AI-, big data-, and FinTech-related expenditures within management expenses. The indicator is accessible, consistent, and comparable across time and institutions, effectively reflecting the relative strength and strategic emphasis of digital transformation. Thus, it serves as a reliable and widely accepted measure under current empirical conditions.

Customer Stickiness–Liability Cost Coupling

The customer stickiness–liability cost coupling variable is constructed as the interaction term between the customer stickiness index and liability cost ratio, representing the joint effect of customer retention and funding cost dynamics. AI enhances customer stickiness through intelligent service systems and scenario-based engagement, which increase user loyalty and reduce churn.

Changes in customer loyalty subsequently influence liability costs, creating an interactive mechanism that links customer behavior with funding efficiency. By examining this coupling effect, the study explores how AI indirectly enhances profitability through the interplay between customer stickiness and liability costs. This analytical framework builds on prior work that examined customer relationship dynamics and their impact on credit cost structures (Loukil & Jarboui, 2015).

Detailed descriptions and definitions of all variables are presented in Table 1 for clarity.

Table 1. Variable definitions.

Variable Type	Variable Name	Symbol	Definition
Dependent Variable	Bank Profitability	Profit	Measures a bank's profitability, typically represented by ROA or ROE.
Independent Variable	Artificial Intelligence	AI × Post	An interaction term capturing the dynamic effect of AI technology adoption by banks.
Mediating Variables	Cost Elasticity of Income	CostElas	Calculated as (year-on-year growth rate of operating income/year-on-year change in cost-to-income ratio) × proportion of administrative expenses, reflecting the elasticity between costs and revenues.
	Deposit–Loan Turnover Adaptability	LoanFit	Measured by (deposit–loan matching ratio × asset profitability efficiency)/year-on-year growth rate of M2, indicating the adaptability of deposit–loan fund flows. Asset Profitability efficiency, measured as net profit divided by total assets, indicates how efficiently a bank converts its assets into profits.
	Multi-Business Capital Allocation Efficiency	DivFit	Defined as $(1 - \text{total loans}/\text{total assets}) \times (\text{total deposits}/\text{total liabilities})$, capturing cross-business capital allocation efficiency and funding stability.

Table 1. Cont.

Variable Type	Variable Name	Symbol	Definition
Moderating Variables	Digital Investment Intensity	DigInvInt	Represents the intensity of resource allocation in digital infrastructure, technology R&D, and platform development, measured by (administrative expenses/total assets).
	Customer Stickiness–Liability Cost Coupling	StickCost	Reflects the interaction between customer loyalty and liability cost, measured as (fee and commission income/operating income) $\times$ (1 – cost-to-income ratio).
Control Variables	Capital Adequacy Ratio	CapAdeqRatio	The ratio of bank capital to risk-weighted assets, indicating the bank’s ability to absorb risk. It includes Core Tier 1 capital—the highest-quality capital composed mainly of common equity and retained earnings—along with Tier 1 and total capital adequacy ratios.
	Capital Strength	CapStr	Measured as (net assets/total assets), representing the bank’s capital structure strength.
	Asset Size	Size	Natural logarithm of total assets, used to indicate the overall scale of the bank.
	Net Interest Margin	NIM	The ratio of net interest income to average interest-earning assets, reflecting the profitability efficiency of interest-bearing assets.
	GDP Growth Rate	GDPG	The year-on-year growth rate of gross domestic product, reflecting macroeconomic performance.
	M2 Growth Rate	M2G	The year-on-year growth rate of broad money supply (M2), reflecting overall monetary liquidity conditions.
	Banking Sentiment Index	BankingSentIndex	A composite index reflecting the overall business conditions and growth expectations of the banking sector, constructed through weighted evaluation of profitability, asset quality, and business expansion indicators.

Note: Data are obtained from the Wind and CSMAR databases.

3.3. Model Specifications

3.3.1. Multi-Period Difference-in-Differences (DID) Model

Given that the adoption of AI in the banking sector occurred gradually across different time periods, this study employs a multi-period difference-in-differences framework to identify the impact of AI adoption on bank profitability, measured by ROA. The baseline empirical model is specified as follows:

$$ROA_{i,t} = \alpha_0 + \alpha_1(AI_{i,t} \times Post_{i,t}) + \sum \alpha_2 Control_{i,t} + \lambda_t + \mu_j + \varepsilon_{i,t} \quad (1)$$

Here, $ROA_{i,t}$ denotes the dependent variable, representing the return on assets of bank i in year t . $AI_{i,t} \times Post_{i,t}$ is the policy interaction term, where $AI_{i,t} = 1$ if bank i has adopted AI technology, and $Post_{i,t} = 1$ for periods after AI adoption. The coefficient α_1 captures the net effect of AI application on bank profitability.

$\text{Control}_{i,t}$ is a vector of control variables capturing bank-specific and macroeconomic characteristics. λ_t , μ_j represent time fixed effects and bank-specific fixed effects, respectively, to control for unobserved temporal and cross-sectional heterogeneity. $\varepsilon_{i,t}$ is the idiosyncratic error term.

3.3.2. Mediation Effect Models

Three regression models are constructed to examine the potential mechanism effects through which AI adoption influences bank profitability (T. Jiang, 2022). The mediating variables include cost elasticity of income (CostElas), deposit–loan turnover adaptability (LoanFit), and multi-business capital allocation efficiency (DivFit). The corresponding models are specified as follows:

$$\text{CostElas}_{i,t} = \beta_0 + \beta_1(\text{AI}_{i,t} \times \text{Post}_{i,t}) + \sum \beta_2 \text{Control}_{i,t} + \lambda_t + \mu_j + \varepsilon_{i,t} \quad (2)$$

$$\text{LoanFit}_{i,t} = \rho_0 + \rho_1(\text{AI}_{i,t} \times \text{Post}_{i,t}) + \sum \rho_2 \text{Control}_{i,t} + \lambda_t + \mu_j + \varepsilon_{i,t} \quad (3)$$

$$\text{DivFit}_{i,t} = \gamma_0 + \gamma_1(\text{AI}_{i,t} \times \text{Post}_{i,t}) + \sum \gamma_2 \text{Control}_{i,t} + \lambda_t + \mu_j + \varepsilon_{i,t} \quad (4)$$

where $\text{CostElas}_{i,t}$, $\text{LoanFit}_{i,t}$ and $\text{DivFit}_{i,t}$ denote the three mechanism variables, representing cost elasticity of income, deposit–loan turnover adaptability, and multi-business capital allocation efficiency, respectively. All other variables are defined as in Model (1).

3.3.3. Moderation Effect Models

To further explore how digital investment intensity and customer stickiness–liability cost coupling moderate the relationship between AI adoption and bank profitability, the baseline DID model is extended by introducing interaction terms. The moderating effect of digital investment intensity is tested as follows:

$$\text{ROA}_{i,t} = \theta_0 + \theta_1(\text{AI} \times \text{Post}) + \theta_2(\text{AI} \times \text{Post} \times \text{DigInvInt}) + \sum \theta_4 \text{Control} + \lambda_t + \mu_j + \varepsilon \quad (5)$$

where DigInvInt denotes digital investment intensity, measured by administrative expenses over total assets. The interaction term $\text{AI} \times \text{Post} \times \text{DigInvInt}$ captures the moderating effect of digital investment intensity. The sign and significance of the coefficient θ_2 indicate the direction and strength of this moderating role (S. Tang et al., 2020).

Similarly, to examine the moderating role of customer stickiness–liability cost coupling (StickCost), the following model is estimated:

$$\text{ROA}_{i,t} = \theta_5 + \theta_1(\text{AI} \times \text{Post}) + \theta_3(\text{AI} \times \text{Post} \times \text{StickCost}) + \sum \theta_6 \text{Control} + \lambda_t + \mu_j + \varepsilon \quad (6)$$

where StickCost represents customer stickiness–liability cost coupling, reflecting the interaction between client retention and liability cost. The coefficient θ_3 measures the extent and direction to which this coupling moderates the effect of AI on profitability.

4. Empirical Analysis

4.1. Descriptive Statistics

The descriptive statistics for all variables are presented in Table 2. The mean value of ROA is 0.696, with a maximum of 1.599 and a minimum of 0.094. The relatively small variation suggests that listed banks exhibit consistent asset utilization efficiency and maintain sound financial performance throughout the sample period.

Table 2. Descriptive statistics of variable.

Variable	N	Mean	Std. Dev.	Min	Max
ROA	986	0.696	0.326	0.094	1.599
AI $\times$ Post	986	0.671	0.470	0.000	1.000
Capital Adequacy Ratio	986	0.128	0.020	0.081	0.249
Capital Strength	986	0.067	0.013	0.024	0.121
Asset Size (ln)	986	10.549	1.231	6.843	12.889
Net Interest Margin	986	2.330	0.416	1.200	3.655
GDP Growth Rate (China)	986	0.073	0.035	−0.069	0.187
M2 Growth Rate	986	0.133	0.051	0.080	0.293
Banking Sentiment Index	986	0.729	0.079	0.583	0.872

The mean value of the DID interaction term AI $\times$ Post is 0.671, suggesting that approximately 67.1% of the observations fall into the “treatment group $\times$ post-adoption period” category. This reflects a substantial degree of AI adoption across banks during the study period, providing a robust empirical basis for identifying the impact of AI implementation on profitability.

The study sample includes 17 Chinese A-share listed commercial banks covering the period 2009–2022. Following the classification of the China Banking and Insurance Regulatory Commission (CBIRC), the banks are grouped into central state-owned, joint-stock, and city commercial categories. The distribution of sample banks is summarized in Table 3.

Table 3. Sample distribution by ownership type.

Ownership Type	Bank Name	Number of Banks	Percentage of Total (%)
Central State-Owned Banks	Agricultural Bank of China (ABC)	5	29.4
	Bank of Communications (BoCom)		
	Industrial and Commercial Bank of China (ICBC)		
	China Construction Bank (CCB)		
	Bank of China (BOC)		
Joint-Stock Commercial Banks	Ping An Bank	8	47.1
	China CITIC Bank		
	China Minsheng Bank		
	China Everbright Bank		
	Industrial Bank		
	China Merchants Bank		
	Huaxia Bank		
City Commercial Banks	Shanghai Pudong Development Bank (SPDB)	3	17.6
	Bank of Beijing		
	Bank of Nanjing		
Other (Policy-Oriented or Mixed Ownership)	Bank of Ningbo	1	5.9
Total		17	100.0

Note: The “Other” category represents institutions with hybrid capital structures or policy-related mandates (if applicable).

4.2. Baseline Regression Results

The difference-in-differences (DID) estimation results indicate that AI adoption exerts a positive and significant effect on bank profitability. When ROA is used as the dependent variable, the coefficient of the core interaction term ($AI \times Post$) remains significantly positive across all model specifications.

The results show that in Column (1) of Table 4, without incorporating control variables, the interaction term exhibits a coefficient of 0.201, which is statistically significant at the 1% level. After further controlling for bank-specific characteristics and macroeconomic factors in Column (2), the coefficient increases to 0.253, remaining highly significant at the 1% level. This consistent significance indicates that the profitability-enhancing effect of AI adoption is robust across different model specifications.

Table 4. The impact of artificial intelligence on bank profitability: baseline regression results.

Variable	(1) ROA	(2) ROA
$AI \times Post$	0.201 *** (4.35)	0.253 *** (5.61)
Capital Adequacy Ratio		3.880 *** (3.70)
Capital Strength		−6.853 *** (−3.82)
Asset Size		−0.345 *** (−5.21)
Net Interest Margin		0.156 *** (3.99)
GDP Growth Rate (China)		0.112 (0.25)
M2 Growth Rate		1.168 ** (2.21)
Banking Sentiment Index		1.595 *** (3.26)
Constant	0.561 *** (17.24)	2.436 *** (2.73)
Bank Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	986	986
R ²	0.161	0.238
Adj. R ²	0.134	0.207
F-statistic	18.937	14.484

Note: t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

From an economic perspective, the estimated coefficient of approximately 0.25 suggests that, *ceteris paribus*, the adoption of AI increases a bank's ROA by about 0.25 percentage points on average. Considering the observed range of ROA in the sample, this magnitude reflects a substantively meaningful improvement in profitability. It implies that AI adoption has tangibly enhanced banks' financial performance by optimizing business processes, improving risk identification efficiency, and augmenting precision in resource allocation.

Overall, these findings provide strong empirical support for Hypothesis 1, confirming that artificial intelligence significantly enhances bank profitability.

4.3. Mediation Effect Analysis

The mediation effect analysis indicates that the baseline regression results of the explanatory variable on the dependent variable remain consistent with the main findings, confirming the validity of the mediating mechanism.

In Column (2) of Table 5, the coefficient of the interaction term $AI \times Post$ on the mediating variable cost elasticity of income is 36.584 and statistically significant at the 1% level, indicating that AI adoption significantly enhances banks' cost-income management efficiency. Through process automation and dynamic resource allocation, AI reduces the rigidity of cost structures by converting part of fixed costs into variable, revenue-responsive costs, thereby improving the adaptability of cost structures to operational fluctuations.

Table 5. Mediation effect test results.

Variable	(1) ROA	(2) Cost-Income Elasticity	(3) Deposit-Loan Turnover Adaptability	(4) Multi-Business Capital Allocation Efficiency
$AI \times Post$	0.253 *** (5.61)	36.584 *** (3.89)	0.007 *** (2.61)	0.012 * (1.83)
Capital Adequacy Ratio	3.880 *** (3.70)	−330.634 (−1.51)	0.114 * (1.71)	−0.019 (−0.13)
Capital Strength	−6.853 *** (−3.82)	390.945 (1.04)	−0.047 (−0.41)	−0.604 ** (−2.35)
Asset Size	−0.345 *** (−5.21)	0.755 (0.05)	−0.018 *** (−4.30)	0.039 *** (4.11)
Net Interest Margin	0.156 *** (3.99)	5.336 (0.66)	0.005 ** (2.18)	0.006 (0.99)
GDP Growth Rate (China)	0.112 (0.25)	−52.734 (−0.56)	0.099 *** (3.48)	−0.105 (−1.63)
M2 Growth Rate	1.168 ** (2.21)	54.215 (0.49)	−0.073 ** (−2.18)	−0.134 * (−1.77)
Banking Sentiment Index	1.595 *** (3.26)	128.113 (1.25)	0.033 (1.07)	0.079 (1.12)
Constant	2.436 *** (2.73)	−130.872 (−0.70)	0.181 *** (3.20)	−0.080 (−0.62)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
N	986	986	986	986
R ²	0.238	0.078	0.411	0.564
Adj. R ²	0.207	0.041	0.387	0.546
F-statistic	14.484	2.663	13.917	7.083

Note: t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Existing research (S. F. Tang & Wu, 2024) has confirmed that cost elasticity of income has a significant positive effect on ROA. Therefore, improved cost efficiency constitutes the primary mediation pathway through which AI enhances bank profitability. Its indirect effect is expected to contribute the largest share of the overall mechanism, highlighting cost flexibility as the most influential transmission channel.

In Column (3), the coefficient of $AI \times Post$ on deposit–loan turnover adaptability is 0.007, also significant at the 1% level, suggesting that AI effectively boosts fund allocation efficiency. By integrating heterogeneous data from customer transactions, consumption,

and credit histories, AI enables precise forecasting of both individual behavior and aggregate financial trends. Consequently, banks can proactively adjust deposit–loan structures and optimize maturity and quota matching.

Consistent with prior evidence (Huang et al., 2024) that deposit–loan turnover adaptability is positively associated with profitability, this pathway represents a structural optimization effect rather than a scale expansion effect. Although the magnitude of the coefficient is relatively moderate, its direction and stability indicate a clear and persistent mediating channel through which AI enhances profitability.

In Column (4), the coefficient of $AI \times Post$ on multi-business capital allocation efficiency is 0.012, significant at the 10% level, implying that AI adoption has a positive impact on cross-business coordination. By integrating client and capital data across various business lines, AI facilitates real-time identification of liquidity surpluses and gaps, thereby enabling dynamic fund reallocation among divisions.

This mechanism reflects AI's complementary role in promoting data integration and capital coordination across business segments, as the indicator has been empirically confirmed to exert a significant positive effect on profitability (S. F. Tang & Wu, 2024). Compared with the previous two channels—cost efficiency and fund allocation efficiency—this mechanism's economic contribution depends more on banks' organizational synergy and digital integration capability. Therefore, while the current effect appears moderate, its potential impact is likely to expand as digital infrastructure matures further.

In summary, all three mediating channels receive empirical support, confirming Hypotheses 2, 3, and 4.

4.4. Moderation Effect Analysis

The results demonstrate that in Column (2) of Table 6, the main effect of digital investment intensity is significantly positive, with a coefficient of 62.511 at the 1% significance level, indicating that digital infrastructure itself enhances bank profitability. Moreover, the interaction term between digital investment intensity and $AI \times Post$ exhibits a coefficient of 47.343, also significant at the 1% level. This suggests that the profitability gains from AI adoption increase with higher levels of digital investment.

Economically, this result implies that greater digital investment strengthens a bank's foundational capabilities in data acquisition, system interoperability, and model deployment, thereby improving the compatibility and synergy between AI technologies and existing operational systems. In banks with more advanced digital foundations, AI-based applications—such as risk management optimization, precision marketing, and operational automation—are more effectively implemented, leading to amplified profitability effects.

In Column (3), the moderating effect of customer stickiness–liability cost coupling is examined. While the main effect of this variable is statistically insignificant, its interaction term with $AI \times Post$ is 1.188 and significant at the 10% level, indicating that the alignment between customer stickiness and liability cost structure influences the strength of AI's profitability enhancement.

Although the statistical magnitude and significance of this moderating effect are relatively modest, its economic interpretation is meaningful: when banks maintain stable, low-cost funding from loyal customer bases, AI's applications in customer segmentation, personalized pricing, and cross-selling become more effective, further improving profitability. The observed marginal significance is consistent with expectations, given the considerable heterogeneity in customer–liability coupling across banks in the sample.

Table 6. Moderation effect test results.

Variable	(1) ROA	(2) ROA	(3) ROA
AI × Post	0.253 *** (5.61)	−0.019 (−0.55)	0.143 (1.32)
Capital Adequacy Ratio	3.880 *** (3.70)	2.601 *** (4.19)	3.627 *** (3.28)
Capital Strength	−6.853 *** (−3.82)	−3.206 *** (−3.00)	−4.778 ** (−2.40)
Asset Size	−0.345 *** (−5.21)	−0.178 *** (−4.51)	−0.227 *** (−2.85)
Net Interest Margin	0.156 *** (3.99)	0.058 ** (2.48)	0.139 *** (3.35)
GDP Growth Rate (China)	0.112 (0.25)	0.235 (0.88)	−0.785 * (−1.69)
M2 Growth Rate	1.168 ** (2.21)	0.487 (1.56)	1.107 ** (2.10)
Banking Sentiment Index	1.595 *** (3.26)	0.124 (0.42)	2.831 *** (5.47)
Digital Investment Intensity		62.511 *** (17.96)	
AI × Post × DigInvInt		47.343 *** (11.07)	
Customer Stickiness–Liability Cost Coupling			−0.525 (−0.82)
AI × Post × StickCost			1.188 * (1.68)
Constant	2.436 *** (2.73)	1.693 *** (3.21)	0.323 (0.33)
Bank Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	986	986	865
R ²	0.238	0.735	0.307
Adj. R ²	0.207	0.723	0.273
F-statistic	14.484	210.120	13.968

Note: t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

All models include bank and time fixed effects, and the estimation results remain stable and robust. Overall, the findings provide empirical support for Hypotheses 5 and 6, confirming that both digital investment intensity and customer stickiness–liability cost coupling serve as effective moderators in the relationship between AI adoption and bank profitability.

4.5. Robustness Tests

4.5.1. Parallel Trend Test

To further validate the robustness and causal interpretation of the DID estimation results, this study conducts a parallel trend test based on an event-study approach. The results are illustrated in Figure 1.

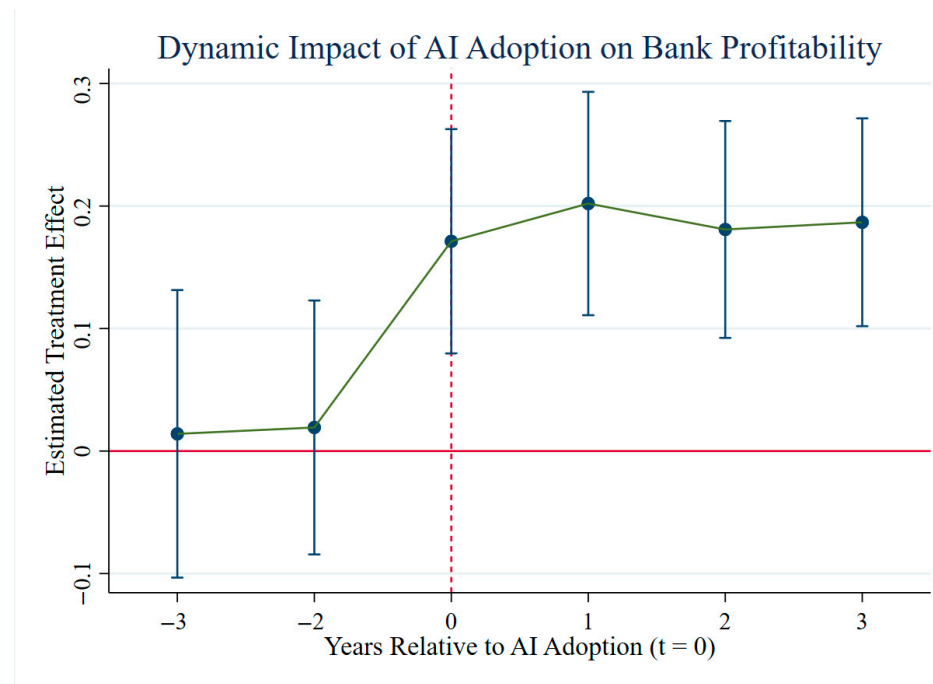


Figure 1. Results of the parallel trend test. The solid line with dots shows the estimated dynamic treatment effects of AI adoption on bank profitability, with vertical bars indicating 95% confidence intervals. The vertical dashed line marks the timing of AI adoption ($t = 0$), and the horizontal solid line denotes the zero-effect benchmark.

Following prior studies (Wang & Liu, 2013), the dummy variable corresponding to the year immediately preceding AI adoption is excluded and serves as the benchmark (reference) period. To mitigate potential multicollinearity, the sample data were standardized prior to estimation.

As shown in Figure 1, the estimated coefficients fluctuate around zero before AI adoption, and their confidence intervals include zero, indicating that there are no systematic differences in profitability trends between the treatment and control groups prior to policy implementation. This finding confirms that the parallel trend assumption holds.

In the three years following AI adoption, both the coefficients and their confidence intervals are consistently positive and statistically significant, suggesting that AI implementation exerts a sustained positive impact on bank profitability during the effective policy period.

Overall, the parallel trend test provides strong empirical evidence that the observed improvement in bank profitability primarily results from AI adoption, rather than from unobserved time-varying factors or pre-existing trends.

4.5.2. Placebo Test

To ensure that the baseline regression results are not driven by random factors, a placebo test was conducted. Specifically, the treatment indicator in the core explanatory variable ($AI \times Post$) was randomly reassigned across the full sample, thereby generating pseudo treatment and control groups. This random assignment was repeated 500 times, and each simulation produced an estimated pseudo policy effect. The distribution of these placebo estimates is presented in Figure 2.

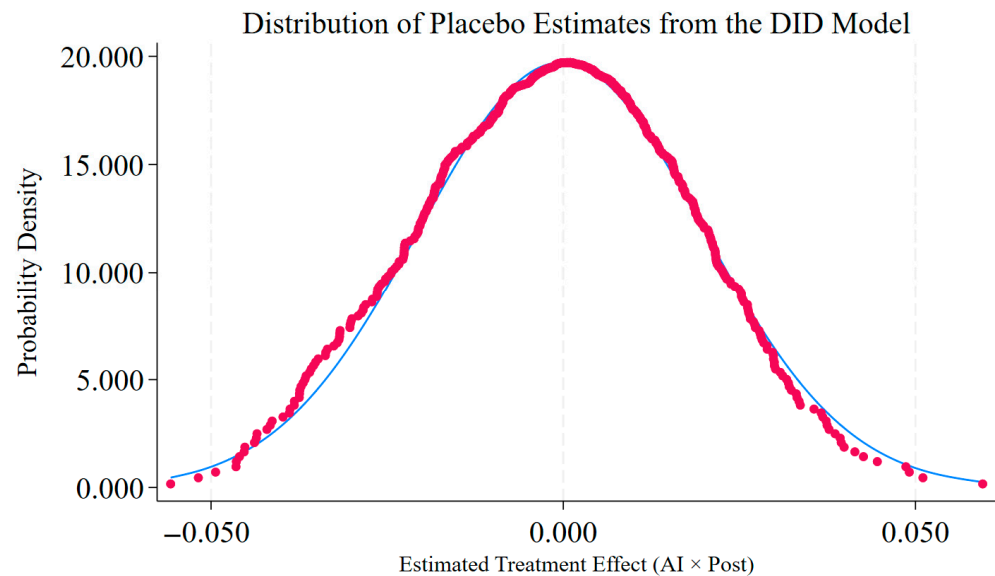


Figure 2. Results of the placebo test. Red dots represent the empirical distribution of placebo DID estimates obtained from repeated random assignments, while the solid blue line shows the corresponding kernel density estimate. The figure illustrates the distribution of estimated treatment effects under the placebo test.

As shown in Figure 2, the estimated pseudo policy effects are approximately normally distributed around zero, with the majority of the estimates clustered near zero and clearly distinct from the actual estimated coefficient obtained from the baseline regression.

This finding indicates that the observed policy effect in the baseline model is not attributable to random noise or spurious correlations, but rather reflects a genuine causal relationship between AI adoption and bank profitability. The placebo test therefore provides further evidence supporting the robustness of the empirical results.

4.5.3. Substitution of the Dependent Variable

To mitigate potential bias arising from the use of a single performance indicator, the dependent variable was replaced with ROE to re-estimate the baseline model.

After replacing the dependent variable with an alternative profitability indicator, the coefficient of the core interaction term remains significantly positive, with a magnitude of 2.715 at the 1% significance level. This result reaffirms the robustness and consistency of the empirical findings, suggesting that the positive effect of AI adoption on bank profitability is stable and not sensitive to the specific measure of profitability employed.

4.5.4. Excluding Special Samples

Considering that the COVID-19 pandemic in 2020 had a substantial impact on the operations and profitability of listed banks, this study conducts an additional robustness check by excluding data after 2020 to ensure the reliability of the results.

The results demonstrate that, following existing empirical practices, we re-estimated the regression using the truncated sample, with the findings reported in Column (2) of Table 7. Specifically, the coefficient of the core interaction term ($AI \times Post$) remains significantly positive at the 1% level, with an estimated value of 0.249, indicating the robustness of the baseline conclusion.

Table 7. Robustness test results.

Variable	(1) ROE	(2) ROA	(3) FROA
AI × Post	2.715 *** (3.41)	0.249 *** (5.51)	0.217 *** (4.76)
Capital Adequacy Ratio	62.803 *** (3.39)	4.531 *** (3.84)	−0.006 (−0.01)
Capital Strength	−297.484 *** (−9.40)	−8.349 *** (−4.23)	−2.219 (−1.20)
Asset Size	−5.253 *** (−4.50)	−0.460 *** (−6.04)	−0.154 ** (−2.25)
Net Interest Margin	4.337 *** (6.31)	0.146 *** (3.38)	0.071 * (1.78)
GDP Growth Rate (China)	−18.161 ** (−2.29)	6.294 *** (7.41)	2.489 *** (5.46)
M2 Growth Rate	21.934 ** (2.36)	2.532 *** (4.65)	0.813 (1.52)
Banking Prosperity Index	64.081 *** (7.41)	−0.351 (−0.62)	−4.284 *** (−8.64)
Constant	18.310 (1.16)	4.414 *** (4.38)	5.004 *** (5.44)
Bank Fixed Effects	No	No	No
Year Fixed Effects	No	No	No
N	986	816	952
R ²	0.380	0.299	0.226
Adj. R ²	0.355	0.267	0.193
F-statistic	23.366	25.489	13.171

Note: t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

This finding suggests that the positive effect of AI adoption on bank profitability persists even after controlling for the potential distortions caused by the pandemic, thereby confirming the stability and robustness of the study's conclusions.

4.5.5. Policy Lag Effect

To examine the lagged impact of AI adoption on bank profitability, the model is re-estimated using the one-period lag of the dependent variable (FROA) as the new dependent variable.

As reported in the results, the coefficient of the core interaction term AI × Post remains significantly positive at the 1% level, indicating that the positive policy effect of AI adoption on bank profitability is persistent over time rather than short-lived.

This finding provides additional evidence supporting the robustness and temporal stability of the baseline results, suggesting that the benefits of AI implementation continue to enhance bank performance in subsequent periods.

4.6. Endogeneity Test

Propensity Score Matching—AI × Post (PSM-DID)

To alleviate potential sample self-selection bias in the estimation results, this study adopts a propensity score matching (PSM) approach combined with the difference-in-differences (DID) model (AI × Post). Four matching algorithms—nearest-neighbor, caliper, radius, and kernel matching—are employed to pair treated and control banks, thereby

testing the causal impact of AI adoption on bank profitability. The regression results are summarized in Table 8.

Table 8. Propensity Score Matching (PSM) results for the impact of AI adoption on bank profitability.

Variable	(1) Nearest Neighbor	(2) Caliper Matching	(3) Radius Matching	(4) Kernel Matching
AI × Post	0.264 * (1.98)	0.253 ** (2.51)	0.242 *** (3.76)	0.201 *** (2.65)
Capital Adequacy Ratio	9.679 * (1.80)	12.084 *** (2.80)	5.870 ** (2.48)	6.085 ** (2.30)
Capital Strength	−20.541 ** (−2.08)	−27.169 *** (−3.51)	−24.233 *** (−4.89)	−25.372 *** (−4.47)
Asset Size	−1.709 *** (−2.72)	−1.755 *** (−4.23)	−1.159 *** (−5.26)	−1.207 *** (−4.57)
Net Interest Margin	0.147 (0.65)	0.176 (1.14)	0.090 (1.11)	0.216 ** (2.21)
GDP Growth Rate (China)	−5.434 (−0.68)	−1.848 (−0.32)	6.626 ** (1.99)	2.693 (0.73)
M2 Growth Rate	−4.668 (−0.91)	−3.673 (−1.04)	−0.183 (−0.09)	−1.260 (−0.55)
Banking Prosperity Index	0.076 (0.04)	−1.070 (−0.73)	0.453 (0.50)	0.656 (0.64)
Constant	18.601 ** (2.37)	19.595 *** (3.78)	12.228 *** (4.26)	12.790 *** (3.74)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
N	97	140	343	249
R ²	0.503	0.484	0.357	0.359
Adj. R ²	0.277	0.330	0.289	0.261
F-statistic	3.578	5.581	10.221	7.463

Note: t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The results demonstrate that the coefficients of the core explanatory variable AI × Post, all four matching methods yield significantly positive coefficients at the 1% or 5% levels (Nearest Neighbor: 0.264, $p < 0.05$; Caliper: 0.253, $p < 0.01$; Radius: 0.242, $p < 0.01$; Kernel: 0.201, $p < 0.01$). These findings indicate that, regardless of the specific PSM algorithm applied, AI adoption consistently enhances bank profitability, which is fully consistent with the baseline DID results.

Examining the control variables, the capital adequacy ratio remains significantly positive across all four matching models, suggesting that stronger capitalization elevates banks' profitability. Conversely, both capital strength and asset size show significant negative coefficients, aligning with the realistic logic that capital expansion or structural adjustment may temporarily compress profitability in the short term. Although the significance and sign of other control variables fluctuate slightly across different matching methods, these variations do not alter the robustness of the core conclusion.

Furthermore, the goodness-of-fit statistics (R^2) and F-statistics of all matching models fall within reasonable ranges, confirming the strong explanatory power and appropriate specification of the PSM–DID framework. Taken together, the results of the PSM–AI × Post estimation further validate that AI adoption exerts a robust and positive effect on bank profitability, mitigating endogeneity concerns related to sample selection bias.

5. Further Discussion

5.1. Bank Ownership Structure

Based on the ownership structure of banks, the sample is classified into three groups: central state-owned banks, local state-owned banks, and publicly listed commercial banks. As shown in the first three columns of Table 9, the coefficients of the core interaction term $AI \times Post$ are positive and statistically significant across all three groups, though the magnitude of the coefficients differs.

Table 9. Heterogeneity test of bank characteristics.

Bank Type/Size/Policy Timing	Bank Ownership Type			Bank Size		Policy Shock Timing	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Central State-Owned Enterprises	Local State-Owned Enterprises	Public Enterprises	Small and Medium-Sized Banks	Large Banks	Before 2013	2013 and After
$AI \times Post$	0.275 *** (3.09)	0.112 (1.64)	0.303 *** (2.62)	0.213 *** (3.75)	0.505 *** (5.31)	0.234 ** (2.15)	0.208 *** (2.91)
Capital Adequacy Ratio	0.267 (0.13)	8.045 *** (5.00)	6.786 ** (2.57)	8.727 *** (6.12)	4.706 ** (2.29)	3.359 ** (2.39)	6.637 *** (3.75)
Capital Strength	−10.737 *** (−2.87)	−20.296 *** (−6.25)	−13.032 *** (−3.00)	−14.909 *** (−5.96)	−14.390 *** (−3.65)	−8.479 *** (−3.31)	−10.186 *** (−3.50)
Asset Size	−1.484 *** (−8.16)	−1.158 *** (−6.47)	−0.470 *** (−3.39)	−0.739 *** (−6.30)	−2.931 *** (−10.43)	−0.382 *** (−4.32)	−0.547 *** (−4.41)
Net Interest Margin	0.139 * (1.89)	0.200 *** (2.76)	0.125 ** (1.98)	0.128 ** (2.11)	0.028 (0.50)	0.227 *** (3.59)	0.094 * (1.79)
GDP Growth Rate (China)	0.619 (0.91)	0.538 (0.73)	−0.181 (−0.21)	−0.144 (−0.19)	1.066 ** (2.03)	0.223 (0.35)	0.028 (0.04)
M2 Growth Rate	0.873 (1.08)	1.491 * (1.68)	1.384 (1.36)	1.622 ** (2.55)	0.410 (0.45)	1.360 * (1.83)	0.948 (1.25)
Banking Prosperity Index	0.164 (0.22)	0.527 (0.64)	2.296 ** (2.42)	2.560 *** (3.69)	−1.417 ** (−2.18)	1.327 * (1.93)	1.736 ** (2.47)
Constant	17.674 *** (7.34)	11.036 *** (5.24)	3.126 * (1.74)	5.048 *** (3.54)	35.322 *** (10.25)	3.152 ** (2.55)	4.322 *** (2.82)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	406	290	290	493	493	522	464
R ²	0.341	0.343	0.250	0.306	0.384	0.263	0.239
Adj. R ²	0.292	0.279	0.176	0.254	0.340	0.218	0.188
F-statistic	11.456	10.632	4.819	15.100	16.150	7.067	7.719

Note: t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Specifically, the coefficient of $AI \times Post$ is highest for publicly listed banks (0.303), followed by central state-owned banks (0.275), while it is relatively lower for local state-owned banks (0.112).

This heterogeneity can be attributed to differences in market orientation, governance efficiency, and resource allocation flexibility among the three ownership types. Publicly listed banks—characterized by stronger market mechanisms and higher managerial autonomy—can respond more swiftly to policy incentives and integrate AI technologies more effectively into operational processes, thereby achieving greater profitability gains. In contrast, state-owned banks, particularly at the local level, are subject to more rigid governance structures and administrative decision-making procedures, which may slow the transmission and realization of policy-driven technological effects (Onana, 2024).

5.2. Bank Size

Based on total asset size, the sample is divided into two groups: small and medium-sized banks and large banks. As reported in Columns (4) and (5) of Table 9, the coefficients of the core interaction term $AI \times Post$ are positive and statistically significant for both

groups. However, the coefficient for small and medium-sized banks (0.213) is lower than that for large banks (0.505).

This result suggests that the profitability-enhancing effect of AI adoption is more pronounced among large banks. A possible explanation is that large banks, endowed with stronger capital capacity and superior resource integration ability, are better positioned to absorb and leverage the policy incentives and technological dividends associated with AI adoption. Consequently, they can achieve greater efficiency gains and profit expansion.

In contrast, small- and medium-sized banks, though characterized by greater operational flexibility and higher policy responsiveness, are constrained by their limited financial capacity and narrower business coverage, which restrict their ability to fully capitalize on the benefits of AI-related policy support. As a result, their estimated coefficients are relatively smaller than those of large banks (Anginer et al., 2018).

5.3. Policy Timing

The year 2013 marks a pivotal policy inflection in China's financial digitalization agenda. Prior to 2013, financial technology initiatives primarily emphasized automation and informatization, as reflected in the Informationization Development Plan for the Financial Industry (2011–2015) issued by the People's Bank of China, which focused on improving electronic banking and core data systems. However, beginning in 2013, the policy orientation shifted toward intelligent finance and the integration of AI-driven technologies. The release of the Guidelines for Smart Finance Development, the Action Plan for the Integration of Artificial Intelligence and the Real Economy (2013–2015), and subsequent programs under the Digital China strategy collectively promoted AI applications in risk management, intelligent customer service, and capital allocation.

This institutional transition justifies the use of 2013 as a valid cutoff point in the heterogeneity analysis. It represents the shift from the experimental phase—dominated by process automation and pilot programs—to the strategic phase of policy-driven AI adoption, during which commercial banks began systematically incorporating AI into core business operations and compliance systems.

As shown in the last two columns of Table 9, the coefficients of the core interaction term $AI \times Post$ are positive and statistically significant in both subsamples. However, the coefficient for the pre-2013 period (0.234) is slightly higher than that for the post-2013 period (0.208).

This difference can be explained by the evolution of policy implementation. Before 2013, the policy framework for AI adoption in the banking sector was in a pilot phase, and the early-stage policy dividends—such as targeted subsidies, tax incentives, and streamlined administrative procedures—produced more immediate and concentrated profitability gains. After 2013, however, as policy objectives shifted toward long-term regulation, risk management, and system-wide standardization, the short-term marginal effect on profitability became relatively weaker, resulting in a slightly smaller coefficient (Galan et al., 2025).

6. Conclusions and Policy Implications

6.1. Research Conclusions and Comparative Discussion

Using a multi-period difference-in-differences (DID) framework combined with propensity score matching (PSM) and extensive robustness checks, this study provides strong causal evidence that AI adoption enhances bank profitability. The results confirm that AI improves profitability primarily through two complementary mechanisms: 1. Operational efficiency enhancement, measured by improvements in cost-income elasticity.

2. Resource allocation optimization, reflected in higher deposit–loan turnover adaptability and multi-business capital allocation efficiency.

These findings are broadly consistent with international studies that link digitalization to performance improvement (Hughes et al., 2022; Sheth et al., 2022; Fraisse & Laporte, 2022). However, while these studies emphasize short-term cost reductions or process automation, our evidence from China demonstrates that AI's profitability effects are structural and persistent, reshaping not only operations but also capital allocation and customer management.

The results also enrich the emerging literature on financial innovation in emerging markets (S. F. Tang & Wu, 2024; Gyau et al., 2024), which often reports context-dependent or institutionally moderated effects. In contrast to the mixed evidence from Western banking systems—where competitive pressures and data privacy constraints limit AI diffusion—the Chinese context reveals that a hybrid institutional environment (policy-driven yet market-responsive) amplifies the efficiency and allocation benefits of AI. This suggests that AI's economic value is not universal but institutionally contingent, depending on governance flexibility, data accessibility, and regulatory alignment.

Ownership- and scale-based heterogeneity further illustrate how institutional and organizational characteristics condition AI's impact. Publicly listed and large banks, with stronger technological resources and strategic autonomy, experience higher profitability elasticity, whereas local state-owned banks, constrained by hierarchical governance and risk aversion, exhibit slower performance translation. This heterogeneity reinforces the notion that organizational adaptability—rather than mere technological adoption—is the decisive factor in realizing AI's financial potential.

Overall, the findings confirm that AI does more than generate incremental performance gains; it reconstructs the profitability architecture of Chinese banks through technological, organizational, and institutional transformation. The results support Schumpeterian innovation theory—showing how technology reorganizes production factors to raise productivity—and financial intermediation theory, which links technological advancement to liquidity coordination and risk–return optimization.

6.2. Policy Implications

Building on the empirical findings and mechanism analysis, this section outlines three AI-specific policy directions that differentiate the implications for regulators, bank management, and technology policymakers. The goal is to promote sustainable and risk-sensitive AI integration rather than generic digitalization.

6.2.1. Implications for Financial Regulators—Governance Alignment and Risk Calibration

The findings show that AI improves banks' profitability primarily through operational efficiency and resource allocation optimization, but its effects vary with governance flexibility. Regulators should therefore design AI-specific prudential guidelines that integrate algorithmic transparency, model validation, and explainable decision-making into supervisory frameworks.

Establishing AI performance-based monitoring indicators—such as cost elasticity of income improvements, liquidity adaptability, and risk-adjusted returns—would enable regulators to distinguish substantive innovation from superficial digitalization.

In addition, the supervision of AI-driven risk control models should focus on bias detection and data ethics to prevent systemic concentration risk from algorithmic homogenization. Regulators could also incentivize cross-bank AI capability sharing led by central state-owned banks, thereby reducing technological inequality among smaller institutions.

6.2.2. Implications for Bank Management—Strategic Integration and Capability Building

For bank executives, the results highlight AI's role as a strategic coordination mechanism, not merely a cost-saving tool. Large banks should embed AI into enterprise-level strategies, linking it to credit allocation, capital coordination, and risk–return optimization across business lines. This requires building AI governance frameworks that align technical design with business objectives, ensuring that models remain auditable and adaptive.

Smaller and local state-owned banks, facing structural rigidity and limited digital resources, should prioritize modular AI solutions—such as intelligent customer service, predictive risk management, and incremental automation—supported by cooperative alliances or shared technology platforms. Strengthening internal data integration and human–AI collaboration can help translate algorithmic gains into sustained profitability rather than short-term digital efficiency.

6.2.3. Implications for Technology Policymakers—Infrastructure and Innovation Ecosystems

From a technology policy perspective, the study underscores the importance of building an AI innovation infrastructure tailored to financial services. Policymakers should promote the development of financial-grade AI models, secure data-sharing environments, and sectoral knowledge graphs that enhance interpretability and compliance.

National programs, such as an AI Application Evaluation and Benchmarking Framework, could standardize performance metrics and facilitate technology diffusion across ownership types and regions. Meanwhile, funding mechanisms—like an AI Transformation Incentive Fund—should link subsidies to quantifiable performance improvements rather than digital spending volume, ensuring that public support effectively enhances technological productivity.

6.3. Limitations and Future Research Directions

Despite providing novel causal evidence, this study has several limitations that offer promising directions for future research.

First, the analysis relies on text-based identification of AI adoption from annual reports, which may not fully capture the depth, quality, or implementation intensity of AI activities. Future research could employ more granular data, such as AI investment expenditure, algorithmic patents, or digital workforce indicators, to better quantify technological transformation.

Second, although the study identifies heterogeneity across ownership types, it does not fully unpack how ownership structure shapes AI adoption behavior and profitability mechanisms. State-owned and market-oriented banks differ fundamentally in their innovation incentives: state-owned banks often adopt AI in response to regulatory or policy directives emphasizing stability and inclusion, while listed and private banks pursue efficiency, market share, and innovation. Future studies should explore these dynamics using comparative institutional frameworks or behavioral modeling, examining how governance, managerial autonomy, and political incentives mediate the AI–profitability relationship.

Third, the sample focuses on 17 listed commercial banks, excluding non-listed, rural, and policy banks. Extending the scope to these institutions would provide valuable insights into AI's contribution to financial inclusion and regional resilience. Moreover, employing nonlinear dynamic models could reveal long-term feedback loops between AI adoption, profitability, and systemic risk.

By integrating institutional context, ownership behavior, and long-term dynamics, future research can deepen understanding of how intelligent transformation shapes both financial performance and systemic stability in evolving digital economies.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
DID	Difference-in-Differences
PSM	Propensity Score Matching
ROA	Return on Assets
ROE	Return on Equity
NIM	Net Interest Margin
GDP	Gross Domestic Product
M2	Broad Money Supply (M2)
RPA	Robotic Process Automation
NLP	Natural Language Processing
LSTM	Long Short-Term Memory
ROI	Return on Investment
NPL	Non-Performing Loan
NAV	Net Asset Value
AI × Post	Interaction Term (AI adoption × Post-adoption period)

Appendix A

Table A1. Keyword dictionary for identifying AI adoption in bank annual reports.

Artificial Intelligence	Computer Vision	Image Recognition
Knowledge Graph	Intelligent Education	Augmented Reality (AR)
Smart Governance	Feature Extraction	Business Intelligence
Intelligent Elderly Care	Support Vector Machine (SVM)	Knowledge Representation
Pattern Recognition	Internet of Things (IoT)	Human–Machine Dialogue
AI Product	Human–Computer Interaction	Data Mining
Smart Banking	Intelligent Customer Service	Virtual Reality (VR)
Autonomous Driving	Unmanned Driving	Smart Finance
Big Data Marketing	Long Short-Term Memory (LSTM)	AI Chip

Table A1. Cont.

Edge Computing	Cloud Computing	Deep Neural Network (DNN)
AI Processor	Deep Learning	Feature Recognition
Intelligent Insurance	Intelligent Retail	Intelligent Healthcare
Intelligent Transportation	Smart Home	Recurrent Neural Network (RNN)
Big Data Risk Control	Robotic Process Automation (RPA)	Wearable Products
Big Data Platform	Augmented Intelligence	Big Data Operation
Machine Translation	Neural Network	Speech Synthesis
Human–Machine Collaboration	Smart Agriculture	Smart Speaker
Convolutional Neural Network (CNN)	Question–Answering System	Reinforcement Learning
Big Data Analytics	Natural Language Processing (NLP)	Big Data Management
Intelligent Computing	Voice Interaction	Machine Learning
Biometric Identification	Speech Recognition	Intelligent Regulation
Intelligent Investment Advisory (Robo-Advisory)	Intelligent Voice	Voiceprint Recognition
Facial Recognition	Intelligent Agent	Big Data Processing
Distributed Computing	Intelligent Sensor	Intelligent Search

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