 

# The impact of artificial intelligence on corporate financial asset allocation: Moderating role of organizational dynamic capabilities


## Abstract

The integration of artificial intelligence (AI) into corporate operations has revolutionized financial decision-making processes, yet our understanding of how AI adoption specifically impacts financial asset allocation remains limited. While existing research has explored AI's role in various financial applications, there is a critical gap in empirically examining the relationship between AI adoption and corporate financial asset allocation, particularly in understanding the organizational capabilities that enable firms to effectively leverage AI technologies. This study investigates this relationship using panel data from 25,811 firm-year observations of Chinese A-share listed companies (2008-2022). Through comprehensive regression analyses, we find that AI adoption significantly enhances corporate financial asset allocation efficiency, with this relationship being distinctly moderated by organizational dynamic capabilities. Notably, absorptive capability exhibits the strongest moderating effect, followed by innovative and adaptive capabilities. These findings advance our understanding of AI's role in corporate finance by demonstrating that the success of AI implementation in financial decision-making is contingent upon firms' underlying organizational capabilities. The results provide valuable insights for managers and policymakers in developing targeted strategies to enhance the effectiveness of AI adoption in corporate financial management.


Keywords: Artificial intelligence adoption; corporate financial asset allocation; absorptive capability; innovative capability; adaptive capability; dynamic capabilities; organizational learning

JEL Classification: G32, O33, M15, L25

## 1. Introduction

The proliferation of artificial intelligence (AI) has fundamentally transformed the landscape of financial services, revolutionizing domains from market analytics to digital payment ecosystems (Berger, 2023; Chen et al., 2023; Makridakis, 2017; Kile, 2013; Popkova & Gulzat, 2020). The integration of AI and machine learning (ML) methodologies has particularly enhanced the precision of financial forecasting through sophisticated approaches incorporating deep learning, reinforcement learning, and hybrid modeling frameworks (Ko & Lee, 2024; Li et al., 2023; Rane et al., 2024; Sahu et al., 2023; Olubusola et al., 2024; Jiang, 2021). While these technological advancements have substantially augmented decision-making capabilities and portfolio optimization strategies within financial institutions, the mechanisms through which AI adoption influences corporate financial asset allocation, along with their moderating factors, remain inadequately understood.

Contemporary scholarship examining AI's influence on corporate governance has documented significant improvements in information symmetry and decision-making efficacy (Cihon et al., 2021; Hilb, 2020; McBride et al., 2022; Manita et al., 2020; Saggu & Ante, 2023). Notably, the emergence of robo-advisory platforms has facilitated personalized asset allocation recommendations aligned with specific risk preferences and investment objectives (Shanmuganathan, 2020; Todd & Seay, 2020). Recent empirical evidence suggests a curvilinear relationship between financial asset allocations and enterprise digital transformation (Shao, 2024), indicating that AI systems extend beyond mere automation to enable data-driven strategic decision-making (Jarrahi, 2018, 2019). Nevertheless, significant challenges persist in effectively differentiating between financially stable corporations and those experiencing financial distress when implementing AI-based approaches to crisis prediction and asset allocation (Shie et al., 2012; Zhao et al., 2023).

To address these critical gaps in the extant literature, this investigation examines three fundamental research questions: First, how does AI adoption impact corporate financial asset allocation practices in terms of efficiency and effectiveness? Second, to what extent do organizational dynamic capabilities (absorptive, innovative, and adaptive capabilities) moderate the relationship between AI adoption and corporate financial asset allocation? Third, which organizational dynamic capability emerges as the most influential moderator in shaping the relationship between AI adoption and financial asset allocation outcomes?

The primary objectives of this study are to empirically examine the direct effect of AI adoption on corporate financial asset allocation, to investigate the moderating role of organizational dynamic capabilities in this relationship, and to compare the strength of the moderating effects of absorptive, innovative, and adaptive capabilities. We hypothesize that AI adoption has a positive impact on corporate financial asset allocation and that this relationship is further strengthened by the presence of strong organizational dynamic capabilities. Moreover, we expect that the moderating effects of absorptive, innovative, and adaptive capabilities may vary in strength, and we aim to identify which capability has the most significant impact on the relationship between AI adoption and corporate financial asset allocation.

To test our hypotheses, we employ panel data regression analysis using a sample of A-share manufacturing listed companies in China from 2008 to 2022. The data are obtained from the database of CSMAR, Wind, and annual reports of listed companies. We measure AI adoption using the natural logarithm of the frequency of words related to artificial intelligence in annual reports of listed companies plus one, and we construct alternative measures using the natural logarithm of the number of AI patents filed by listed companies in the year plus one. Organizational dynamic capabilities are measured using proxies for absorptive, innovative, and adaptive capabilities.

This study offers several significant contributions to the literature. First, it advances the theoretical understanding of AI's role in corporate finance by providing novel empirical evidence on the causal relationship between AI adoption and financial asset allocation efficiency. Second, it extends the dynamic capabilities framework by demonstrating how different organizational capabilities—absorptive, innovative, and adaptive—distinctly moderate the effectiveness of AI implementation in financial decision-making. Third, by quantifying and comparing the relative influence of these capabilities, this research identifies the critical organizational mechanisms that optimize AI deployment in corporate finance. The findings yield important practical implications: they inform executives about the organizational prerequisites for successful AI integration, guide policymakers in developing frameworks that foster technological adoption, and provide investors with insights into evaluating firms' AI readiness. Additionally, this study establishes a methodological foundation for future research examining the intersection of technological innovation and corporate financial management.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive review of the relevant literature on AI adoption, corporate financial asset allocation, and organizational dynamic capabilities, and develops the hypotheses. Section 3 describes the data, variables, and methodology used in the empirical analysis. Section 4 presents the results and discusses the findings. Section 5 concludes the paper by summarizing the main contributions, limitations, and avenues for future research.

## 2. Literature review

### *2.1 AI and corporate financial asset allocation*

The emergence of artificial intelligence as a cornerstone of digital transformation has fundamentally reshaped corporate operations, particularly in financial asset allocation strategies (Barroso & Laborda, 2022; Brandl & Hornuf, 2020). Although scholars have extensively documented digitalization's broader impact on corporate financial management, a granular examination of AI's specific influence on asset allocation decision-making processes remains imperative for advancing our understanding of this technological evolution.

Contemporary empirical research has illuminated the multifaceted benefits of digital transformation in corporate finance. Chen & Yang (2024) demonstrate that digital transformation catalyzes corporate innovation through dual mechanisms: alleviating financial constraints and enhancing governance structures. Their findings suggest that digitalization serves as a strategic enabler for both operational optimization and innovative capacity. Complementing this perspective, Feng et al. (2023) establish that digital finance's positive influence on financial asset allocation transcends organizational scale, revealing the pervasive nature of digital transformation in reshaping financial strategy formulation.

Further substantiating these insights, Abbas et al. (2024) present robust empirical evidence linking digital finance to enhanced corporate value creation. Their findings elucidate how the integration of digital technologies, particularly AI-driven solutions, yields quantifiable improvements in corporate valuation and competitive positioning. This empirical foundation underscores the strategic imperative of technological integration in contemporary financial management practices.

However, while these findings offer valuable insights into the impact of digitalization on corporate finance, they do not specifically address the unique role of AI in financial asset allocation. As Li (2024) points out, there is a need for further research to understand how enterprise digital transformation influences financial investments, highlighting the complexity of the relationship between digital technologies and asset management.

AI, as a key driver of digital transformation, has the potential to revolutionize financial asset allocation by leveraging advanced data analytics, machine learning, and predictive modeling techniques (Scardovi, 2017). AI-powered systems can process vast amounts of financial data, identify patterns, and generate insights that can inform asset allocation decisions (Olubusola, 2024). By automating complex financial analyses and providing data-driven recommendations, AI can enhance the accuracy and efficiency of asset allocation strategies, ultimately leading to improved financial performance (Barile, 2024).

Furthermore, AI can play a crucial role in risk management within the context of financial asset allocation. As Xin et al. (2022) noted, digital finance can mitigate the risk of corporate bankruptcy by improving information disclosure and reducing financial leverage. AI-driven risk assessment models can analyze various risk factors, such as market volatility, credit risk, and liquidity risk, enabling corporations to make more informed and prudent asset allocation decisions.

Despite the growing recognition of AI's potential in financial asset allocation, empirical research specifically examining the impact of AI adoption on corporate financial asset allocation remains limited. While studies have explored the broader effects of digitalization on corporate finance, there is a gap in understanding the specific mechanisms through which AI influences asset allocation decisions and outcomes.

Based on the existing literature and the transformative potential of AI in the financial domain, we propose the following hypothesis:

***H1:*** *AI adoption has a positive impact on corporate financial asset allocation.*

### *2.2 The role of organizational dynamic capabilities*

Organizational dynamic capabilities refer to a firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Teece et al., 1997; Barreto, 2009; Liu et al., 2024; Hu & Sun, 2024). These capabilities are crucial for firms to adapt to technological advancements, such as AI and digitalization, which significantly impact corporate financial asset allocation (Yang et al., 2019). In the context of AI and financial decision-making, three specific dynamic capabilities—absorptive, innovative, and adaptive capabilities—play a vital role in moderating the relationship between AI adoption and corporate financial asset allocation.

Absorptive capability, defined as a firm's capacity to identify, assimilate, and apply new knowledge effectively (Cohen & Levinthal, 1990; Cousins, 2018; Wang et al., 2024), is essential in the realm of AI and digitalization (Xie et al., 2024). It enables firms to acquire and utilize new knowledge related to AI technologies, integrate it into their existing financial processes, and leverage it to make more informed decisions regarding financial asset allocation (Climent & Palacio, 2017). Firms with higher absorptive capability are better equipped to understand and apply AI-driven insights, leading to enhanced financial performance (Jansen et al., 2005).

Innovative capability, which focuses on a firm's ability to generate novel ideas and technologies to enhance competitiveness (Hurley & Hult, 1998; Aas & Breunig, 2017), complements absorptive capability in the context of AI and financial asset allocation. This capability empowers firms to develop creative solutions and strategies that leverage AI and digitalization for optimal asset allocation (Zahra et al., 2006). Firms with strong innovative capabilities are more likely to experiment with and deploy cutting-edge AI technologies, resulting in improved financial decision-making and outcomes (Calantone et al., 2002).

Adaptive capability, which involves a firm's capacity to adjust and respond to changes in the business environment (Chakravarthy, 1982; Bag et al., 2023), further enhances the dynamics between AI and corporate financial asset allocation. This capability ensures that firms can flexibly adjust their financial asset allocation strategies based on the evolving technological landscape (Sullivan & Wamba, 2024). Firms with higher adaptive capability are better positioned to exploit the benefits of AI in dynamic and uncertain environments, leading to more agile and effective asset allocation decisions

(Uzkurt et al., 2024; Liu et al., 2024).

The complex interrelationship among AI implementation, digital transformation, and corporate financial asset allocation highlights the fundamental importance of dynamic capabilities in contemporary business environments (Leso et al., 2024). This relationship manifests through three distinct but interconnected organizational capabilities. First, absorptive capability serves as a crucial mechanism through which firms assimilate and operationalize AI technologies within their financial decision-making architecture (Campos-Climent & Sanchis-Palacio, 2017; Neirotti et al., 2021). Second, innovative capability enables organizations to conceptualize and implement novel solutions that harness AI and digital technologies for strategic asset allocation optimization (Akter et al., 2023; Zahra et al., 2006). Third, adaptive capability enables firms to reconfigure their asset allocation frameworks in response to technological evolution, thereby sustaining their competitive advantage in dynamic market conditions (Sullivan & Wamba, 2024; Zhou & Li, 2020).

Drawing upon these theoretical underpinnings and the demonstrated potential of dynamic capabilities to enhance AI implementation efficacy in financial decision-making, we develop our research hypotheses. These hypotheses examine the distinctive roles of absorptive, innovative, and adaptive capabilities in moderating the relationship between AI adoption and financial asset allocation effectiveness.

***H2:*** *Absorptive capability moderates the positive relationship between AI adoption and corporate financial asset allocation.*

***H3:*** *Innovative capability moderates the positive relationship between AI adoption and corporate financial asset allocation.*

***H4:*** *Adaptive capability moderates the positive relationship between AI adoption and corporate financial asset allocation.*

Based on the proposed hypotheses and the reviewed literature, we have developed an analytical framework that illustrates the relationships between AI adoption, organizational dynamic capabilities (absorptive, innovative, and adaptive capabilities), and corporate financial asset allocation, as shown in Figure 1. This framework serves as a visual representation of the key variables and their hypothesized interactions, guiding our empirical investigation into the impact of AI on financial decision-making and the moderating role of dynamic capabilities. The framework also incorporates control variables that may influence the relationships under study, such as firm size, leverage, profitability, and corporate governance factors. Additionally, we consider the potential heterogeneity in the relationships across different stages of the firm life cycle (growing, maturing, and declining) to uncover nuanced insights into how the impact of AI adoption and the moderating effects of dynamic capabilities on financial asset allocation may vary depending on the firm's developmental stage.

*[Insert Figure 1 here]*

## 3. Methodology

### *3.1 Data and variable*

Our empirical analysis employs a comprehensive dataset of Chinese A-share listed companies spanning from 2008 to 2022. We construct this dataset by synthesizing information from multiple authoritative sources: the China Stock Market and Accounting Research (CSMAR) database, the Wind Financial Terminal, and companies' annual reports. To mitigate the impact of extreme values and potential outliers, we winsorize all continuous variables at the 1st and 99th percentiles. Following standard practice in corporate finance research, we exclude observations with significant missing data to ensure the robustness of our empirical analyses. The final sample consists of 25,811 firm-year observations, providing a rich empirical setting for examining the relationship between AI adoption and financial asset allocation.

Table 1 presents the definitions and measurements of the variables employed in this study. The explained variable, corporate financial asset allocation (FIN), is calculated as the sum of financial assets for trading, derivative financial assets, available-for-sale financial assets, held-to-maturity investments, long-term equity investments, and investment properties, divided by total assets. Additionally, we construct a dummy variable (FIN2) as an alternative measure, which takes the value of 1 if firm i holds financial assets in year t, and 0 otherwise.

[Insert Table 1 here]

The explanatory variable, AI adoption (AI), is measured using the natural logarithm of the frequency of words related to artificial intelligence in the annual reports of listed companies plus one. We also use an alternative measure (AI_patent), which is the natural logarithm of the number of AI patents filed by listed companies in the year plus one.

The moderating variables, representing organizational dynamic capabilities, include absorptive capability (Absorb), innovative capability (Innovate), and adaptive capability (Adapt). Absorptive capability is measured as the ratio of the company's annual R&D expenditures to operating revenues. Innovative capability is measured using a comprehensive evaluation of the ratio of R&D investment to operating income and the ratio of technical staff to total employees. The data for these two indicators are standardized separately and then summed to obtain the index of enterprise innovation capacity. Adaptive capability is measured using the coefficients of variation of the three major expenditures: R&D expenditures, capital expenditures, and advertising expenditures. These coefficients reflect the degree of flexibility in resource allocation and thus measure the adaptive capacity of the firms. As the results are negative indicators, the values are taken as negative, with larger values indicating greater adaptive capacity.

The control variables include firm size (Size), liability-to-asset ratio (Lev), long-term capital gearing (DLCR), profitability (ROE), cash flow ratio (Cashflow), net profit growth rate (NetGrowth), capital intensity (CAP), financial leverage (FL), Tobin's Q (TobinQ), managerial financial background (FinBack), managerial compensation (Compen), and financing constraints (SA). These variables are measured using standard accounting and financial ratios, as detailed in Table 1.

By employing this comprehensive set of variables and a large sample of Chinese A-share listed companies, this study aims to provide robust empirical evidence on the impact of AI adoption on corporate financial asset allocation and the moderating role of organizational dynamic capabilities.

### *3.2 Model setting*

In order to investigate the impact of AI adoption on corporate financial asset allocation, we construct the following baseline regression model:

$$FIN_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \gamma Controls_{i,t} + YearFE + IndustryFE + \varepsilon_{i,t} \quad (1)$$

Where, $FIN_{i,t}$ represents the financial asset allocation of firm i in year t; $AI_{i,t}$ is the measure of AI adoption for firm i in year t; $Controls_{i,t}$ is a vector of control variables, including firm size, liability-to-asset ratio, long-term capital gearing, profitability, cash flow ratio, net profit growth rate, capital intensity, financial leverage, Tobin's Q, managerial financial background, managerial compensation, and financing constraints; YearFE and IndustryFE represent year and industry fixed effects, respectively; and $\varepsilon_{i,t}$ is the error term.

Next, to examine the moderating effects of organizational dynamic capabilities on the relationship between AI adoption and corporate financial asset allocation, we construct moderating effect models by using interaction terms of dynamic capability and AI. The models can be expressed as below:

Absorptive Capability:

$$FIN_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 Absorb_{i,t} + \beta_3 AI_{i,t} * Absorb_{i,t} + \gamma Controls_{i,t} + YearFE + IndustryFE + \varepsilon_{i,t} \quad (2)$$

Innovative Capability:

$$FIN_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 Innovate_{i,t} + \beta_3 AI_{i,t} * Innovate_{i,t} + \gamma Controls_{i,t} + YearFE + IndustryFE + \varepsilon_{i,t} \quad (3)$$

Adaptive Capability:

$$FIN_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 Adapt_{i,t} + \beta_3 AI_{i,t} * Adapt_{i,t} + \gamma Controls_{i,t} + YearFE + IndustryFE + \varepsilon i,t \quad (4)$$

In these models, $\beta_1$, $\beta_2$, $\beta_3$ captures the moderating effect of three dynamic capabilities on corporate financial asset allocation.

### *3.3 Summary statistics*

Table 2 presents the descriptive statistics for the variables used in the study, based on a sample of 25,811 firm-year observations. The explained variable, FIN (corporate financial asset allocation), has a mean value of 0.0450, indicating that, on average, firms allocate around 4.5% of their total assets to financial assets. The explanatory variable, AI (AI adoption), has a mean value of 0.993, with a substantial variation across firms. The moderating variables, Absorb (absorptive capability), Innovate (innovative capability), and Adapt (adaptive capability), have mean values of 0.0540, 1.135, and -0.628, respectively, suggesting moderate levels of absorptive and innovative capabilities and a relatively lower adaptive capability among the sample firms. The control variables, including Size, Lev, Cashflow, CAP, FL, FinBack, Compen, and SA, exhibit varying levels of dispersion and central tendencies, providing insights into the characteristics of the sample firms. The descriptive statistics imply that there is considerable heterogeneity among the firms in terms of their AI adoption, financial asset allocation, organizational dynamic capabilities, and other firm-specific factors, setting the stage for a comprehensive analysis of the relationships between these variables.

[Insert Table 2 here]

### *3.4 Multilinearity check*

To check for multicollinearity among the independent variables, we calculate the variance inflation factor (VIF) for each variable. Table 3 presents the VIF values and their reciprocals (1/VIF) for the key variables in our study.

[Insert Table 3 here]

The VIF values range from 1.040 to 2.160, with a mean of 1.400. As a general rule of thumb, VIF values greater than 10 indicate a high degree of multicollinearity (Hair et al., 2010). In our case, all VIF values are well below this threshold, suggesting that multicollinearity is not a severe issue in our dataset.

Our diagnostic analysis of variance inflation factors (VIFs) confirms the absence of severe multicollinearity among our predictor variables. The maximum VIF value of

2.160 falls substantially below the conventional threshold of 10, indicating minimal correlation among independent variables. The mean VIF of 1.400 further substantiates the statistical independence of our predictors. These diagnostics provide robust evidence for the stability of our regression estimates and validate the distinct effects captured by our focal variables—AI adoption and the three organizational dynamic capabilities (absorptive, innovative, and adaptive). The low VIF values particularly strengthen our ability to isolate and interpret the individual and interactive effects in our moderation analyses.

## 4. Results and discussions

### *4.1 Baseline regression result*

Table 4 presents the baseline regression results for the impact of AI adoption on corporate financial asset allocation. We estimate two specifications: column (1) includes only the explanatory variable (AI) without any control variables, while column (2) includes a set of control variables to account for firm-specific characteristics that may influence financial asset allocation decisions.

[Insert Table 4 here]

In both specifications, the coefficient of AI is positive and statistically significant at the 5% level in column (1) and at the 1% level in column (2). These results indicate that AI adoption has a positive impact on corporate financial asset allocation, supporting our first hypothesis (H1). The magnitude of the coefficient in column (2) suggests that a one-unit increase in AI adoption leads to a 0.002 unit increase in the proportion of financial assets to total assets, holding other factors constant.

The inclusion of control variables in column (2) improves the explanatory power of the model, as indicated by the increase in R-squared from 0.148 in column (1) to 0.196 in column (2). The control variables exhibit significant relationships with corporate financial asset allocation, consistent with prior literature. Firm size (Size), cash flow (Cashflow), capital intensity (CAP), financial leverage (FL), managerial financial background (FinBack), and managerial compensation (Compen) are positively associated with financial asset allocation, while liability-to-asset ratio (Lev) and financing constraints (SA) are negatively related to financial asset allocation.

Our findings regarding AI adoption's positive influence on financial asset allocation align with and extend prior research on AI's transformative role in financial decision-making (Duan et al., 2019; Jarrahi, 2018). The empirical results demonstrate how AI's advanced computational capabilities facilitate the extraction of meaningful patterns from complex financial datasets, enabling more sophisticated asset allocation strategies (Aziz et al., 2022; Gu et al., 2020). These technological capabilities manifest in enhanced decision precision and temporal efficiency, ultimately yielding superior financial outcomes and more robust risk management frameworks (Huang et al., 2022).

The theoretical underpinnings of this relationship can be effectively interpreted through the resource-based view (RBV) of strategic management (Newbert, 2007; Lockett et al., 2009). The RBV framework posits that sustainable competitive advantage emerges from resources characterized by value, rarity, inimitability, and non-substitutability. In this context, AI technologies, coupled with their complementary human capital and organizational architecture, constitute a strategically valuable resource bundle that enhances financial decision-making efficacy (D'Acunto & Rossi, 2023). This theoretical lens illuminates how AI adoption creates organizational differentiation and value generation through sophisticated asset allocation mechanisms that competitors find difficult to replicate.

### *4.2 Robustness analysis*

To address potential endogeneity concerns that might affect the relationship between AI adoption and financial asset allocation, we employ multiple econometric approaches. Table 5 presents the results from our endogeneity tests using two-stage least squares (2SLS) estimation and Heckman's two-step procedure.

[Insert Table 5 here]

In the first-stage regression (Column 1), we utilize the lagged AI adoption (L.AI) as an instrumental variable, following established practice in corporate finance literature. The highly significant coefficient (0.817, $t = 191.476$) and substantial R-squared (0.816) suggest that our instrument satisfies the relevance criterion.

The second-stage results (Column 2) demonstrate that the positive relationship between AI adoption and financial asset allocation persists ($\beta = 0.002$, $p < 0.01$) after controlling for potential endogeneity. The consistency of this coefficient with our baseline findings suggests that endogeneity does not substantially bias our main results.

The Heckman two-step estimation (Column 3) further validates our findings by accounting for potential selection bias. The significant inverse Mills ratio (imr1 = 0.078, $p < 0.01$) indicates the presence of selection effects, yet the AI coefficient remains positive and significant ($\beta = 0.008$, $p < 0.01$). The larger magnitude in the Heckman model suggests that our baseline estimates may be conservative.

Next, Table 6 presents the results of robustness checks for the impact of AI adoption on corporate financial asset allocation. The robustness checks are performed using alternative measures of AI and financial asset allocation, alternative model specifications, and a subsample excluding the epidemic year.

[Insert Table 6 here]

In the column (1), we use an alternative measure of AI adoption (AI_patent), which is the natural logarithm of the number of AI patents filed by listed companies in the year plus one. The coefficient of AI_patent is positive and statistically significant at the 1% level, consistent with our main findings. This suggests that our results are robust to alternative measures of AI adoption.

The column (2) uses an alternative measure of financial asset allocation (FIN2), which is a dummy variable that takes the value of 1 if a firm holds financial assets in a given year and 0 otherwise. The coefficient of AI remains positive and statistically significant at the 1% level, indicating that our results are robust to alternative measures of financial asset allocation.

In the column (3), we employ an alternative model specification by estimating a random effects model instead of a fixed effects model. The coefficient of AI remains positive and statistically significant at the 1% level, suggesting that our results are robust to alternative model specifications.

The column (4) excludes observations from the epidemic year to address potential concerns that the COVID-19 pandemic may have influenced the relationship between AI adoption and financial asset allocation. The coefficient of AI remains positive and statistically significant at the 1% level, indicating that our results are not driven by the exceptional circumstances of the epidemic year.

The comprehensive suite of robustness tests substantiates the stability and reliability of our primary findings. The documented positive relationship between AI adoption and corporate financial asset allocation remains statistically significant and economically meaningful across multiple analytical dimensions: alternative variable measurements, diverse econometric specifications, and varying temporal frameworks. The consistency of results across these methodological variations provides compelling evidence for the robustness of our empirical findings. Furthermore, these validation exercises reinforce our broader theoretical arguments regarding AI's transformative role in reshaping corporate financial decision-making architecture (Aziz et al., 2022; Gu et al., 2020; Hilb, 2020). The convergence of evidence across multiple analytical approaches strengthens our confidence in the fundamental relationship between AI adoption and financial asset allocation efficiency.

### *4.3 The moderating effect of absorptive capability*

Table 7 examines the moderating effect of absorptive capability on the relationship between AI adoption and corporate financial asset allocation. Column (1) reproduces the baseline regression results for comparison, while column (2) includes the interaction term between AI adoption and absorptive capability (AI*Absorb).

[Insert Table 7 here]

The coefficient of the interaction term AI*Absorb is positive and statistically significant at the 1% level, indicating that absorptive capability positively moderates the impact of AI adoption on financial asset allocation. This finding supports our second hypothesis (H2) and suggests that firms with higher absorptive capability can better leverage AI technologies to enhance their financial decision-making processes and optimize their asset allocation strategies.

The moderating influence of absorptive capability can be theoretically anchored in the dynamic capabilities paradigm (Teece et al., 1997; Zahra & George, 2002). This framework illuminates how organizational capabilities evolve to address rapidly changing technological environments. Specifically, absorptive capability—conceptualized as an organization's capacity to evaluate, internalize, and commercialize external knowledge (Cohen & Levinthal, 1990)—emerges as a critical mediating mechanism in the AI-financial decision making nexus. This capability operates through three distinct but interconnected processes: knowledge recognition, knowledge integration, and knowledge application.

Organizations possessing superior absorptive capability demonstrate enhanced proficiency in identifying valuable AI-related knowledge, synthesizing it with their existing cognitive frameworks, and deploying it to optimize financial decision architectures (Jansen et al., 2005; Todorova & Durisin, 2007). This theoretical mechanism elucidates why firms with comparable levels of AI adoption may achieve divergent financial outcomes based on their underlying absorptive capacity.

Moreover, the positive moderating effect of absorptive capability highlights the importance of complementary organizational capabilities in realizing the full potential of AI in corporate finance (Magistretti et al., 2019; Mikalef et al., 2019). By developing and nurturing absorptive capability, firms can create a conducive organizational environment for the effective adoption and utilization of AI technologies, leading to improved financial performance and competitive advantage.

### *4.4 The moderating effect of innovative capability*

Table 8 examines the moderating effect of innovative capability on the relationship between AI adoption and corporate financial asset allocation. Column (1) presents the baseline regression results, while column (2) includes the interaction term between AI adoption and innovative capability (AI*Innovate).

[Insert Table 8 here]

The coefficient of the interaction term (AI*Innovate) is positive and statistically significant at the 1% level, indicating that innovative capability positively moderates the impact of AI adoption on financial asset allocation. This finding supports our third hypothesis (H3) and suggests that firms with higher innovative capability can better leverage AI technologies to enhance their financial decision-making processes and optimize their asset allocation strategies.

The moderating effect of innovative capability can be explained through the lens of the dynamic capabilities framework (Teece et al., 1997; Zahra & George, 2002). Innovative capability, which refers to a firm's ability to generate, accept, and implement new ideas, processes, products, or services (Hurley & Hult, 1998), is a crucial dynamic capability that enables firms to effectively integrate and utilize AI technologies in their financial decision-making processes. Firms with higher innovative capability are better equipped to develop novel AI-driven financial tools and strategies, leading to improved financial performance and competitive advantage (Calantone et al., 2002; Joshi et al., 2010).

Moreover, the positive moderating effect of innovative capability highlights the importance of complementary organizational capabilities in realizing the full potential of AI in corporate finance (Magistretti et al., 2019; Mikalef et al., 2019). By fostering a culture of innovation and investing in the development of innovative capabilities, firms can create a conducive environment for the effective adoption and utilization of AI technologies in the financial domain.

### *4.5 The moderating effect of adaptive capability*

Table 9 examines the moderating effect of adaptive capability on the relationship between AI adoption and corporate financial asset allocation. Column (1) presents the baseline regression results, while column (2) includes the interaction term between AI adoption and adaptive capability (AI*Adapt).

[Insert Table 9 here]

The coefficient of the interaction term (AI*Adapt) is positive and statistically significant at the 5% level, indicating that adaptive capability positively moderates the impact of AI adoption on financial asset allocation. This finding supports our fourth hypothesis (H4) and suggests that firms with higher adaptive capability can better leverage AI technologies to enhance their financial decision-making processes and optimize their asset allocation strategies in dynamic environments.

The theoretical underpinning of adaptive capability's moderating effect is firmly grounded in the dynamic capabilities framework (Teece et al., 1997; Wang & Ahmed, 2007). This theoretical lens reveals how adaptive capability—conceptualized as an organization's proficiency in detecting and exploiting emergent market opportunities (Chakravarthy, 1982)—functions as a critical organizational mechanism that enhances the effectiveness of AI implementation in financial decision-making under dynamic market conditions. Organizations exhibiting superior adaptive capabilities demonstrate enhanced agility in reconfiguring their AI-driven financial strategies in response to environmental shifts, thereby achieving superior financial outcomes and sustained competitive positions (Oktemgil & Greenley, 1997; Zhou & Li, 2010).

This moderating effect operates through dual mechanisms. First, adaptive capability enables organizations to maintain strategic flexibility in their AI deployment strategies, facilitating rapid adjustments to changing market dynamics. Second, it enhances organizational resilience in volatile financial markets by enabling real-time calibration of AI-driven decision frameworks (Mikalef et al., 2019; Qaiyum & Wang, 2018). These complementary processes create an organizational architecture that optimizes AI utilization across varying market conditions, thereby enhancing the robustness of financial decision-making systems.

### *4.6 Comparison of the moderating effects*

Figure 2 presents a visual comparison of the moderating effects of absorptive capability, innovative capability, and adaptive capability on the relationship between AI adoption and corporate financial asset allocation. The graphs plot the marginal effect of AI adoption on financial asset allocation (FIN) across different levels of each dynamic capability, ranging from low (-1.5 standard deviations) to high (+1.5 standard deviations).

[Insert Figure 2 here]

Graph (1) illustrates the moderating effect of absorptive capability. The positive slope of both lines indicates that the impact of AI adoption on financial asset allocation is positive across all levels of absorptive capability. However, the steeper slope of the high-absorb line compared to the low-absorb line suggests that the positive impact of AI adoption on financial asset allocation is stronger for firms with higher levels of absorptive capability.

Graph (2) depicts the moderating effect of innovative capability. The positive slope of the high-innovate line and the negative slope of the low-innovate line indicate that the impact of AI adoption on financial asset allocation is positive for firms with high levels of innovative capability but negative for firms with low levels of innovative capability. This finding suggests that innovative capability plays a crucial role in enabling firms to leverage AI technologies effectively for financial asset allocation.

Graph (3) shows the moderating effect of adaptive capability. The positive slope of the high-adapt line and the negative slope of the low-adapt line indicate that the impact of AI adoption on financial asset allocation is positive for firms with high levels of adaptive capability but negative for firms with low levels of adaptive capability. This result highlights the importance of adaptive capability in allowing firms to adjust their AI-driven financial strategies in response to changing market conditions.

Comparing the three graphs, we observe that the moderating effect of absorptive capability is the strongest, as evidenced by the steeper slope of the high-absorb line compared to the high-innovate and high-adapt lines. This finding suggests that absorptive capability plays the most critical role in shaping the relationship between AI adoption and financial asset allocation, followed by innovative capability and adaptive capability.

### *4.7 Heterogeneity analysis*

Following the established theoretical frameworks of Anthony and Ramesh (1992) and DeAngelo et al. (2006), we employ a comprehensive approach to classify firms into distinct life cycle stages. Our classification methodology integrates multiple financial indicators to capture the multifaceted nature of organizational development and ensure robust stage identification. Table 10 presents the results of a heterogeneity check that examines the impact of AI adoption on corporate financial asset allocation across different stages of the firm life cycle: growing stage, maturing stage, and declining stage. This analysis helps to uncover potential variations in the relationship between AI adoption and financial asset allocation depending on the developmental stage of the firm.

[Insert Table 10 here]

In the growing stage subsample, the coefficient of AI is positive and statistically significant at the 1% level, indicating that AI adoption has a strong positive impact on financial asset allocation for firms in the growth phase. This finding suggests that growing firms can particularly benefit from AI technologies in optimizing their financial asset allocation strategies, possibly due to their greater flexibility, adaptability, and openness to technological innovations (Koberg et al., 1996; Sørensen & Stuart, 2000).

In the maturing stage subsample, the coefficient of AI is also positive and statistically significant, but at the 10% level, suggesting a weaker positive impact of AI adoption on financial asset allocation for mature firms compared to growing firms. This finding is consistent with the notion that mature firms may face greater organizational inertia and resistance to change, which can limit their ability to fully leverage AI technologies in financial decision-making (Hannan & Freeman, 1984; Kelly & Amburgey, 1991).

In the declining stage subsample, the coefficient of AI is positive but not statistically significant, indicating that AI adoption does not have a significant impact on financial asset allocation for firms in the decline phase. This finding suggests that declining firms may face other pressing challenges and constraints that limit their ability to effectively implement and benefit from AI technologies in financial decision-making (Cameron et al., 1987; Whetten, 1987).

The control variables exhibit varying patterns of significance across the three subsamples, highlighting the heterogeneous effects of firm characteristics on financial asset allocation depending on the firm life cycle stage. For example, firm size (Size) has a stronger positive impact on financial asset allocation for declining firms compared to growing and mature firms, while cash flow (Cashflow) has a stronger positive impact for mature firms compared to growing and declining firms.

The heterogeneity analysis yields several nuanced insights regarding the relationship between AI adoption and corporate financial asset allocation across organizational life cycle stages. Our empirical results demonstrate a systematic variation in this relationship contingent upon firms' developmental phases. Specifically, growing-stage firms exhibit the most pronounced positive association ($\beta = 0.002$, $p < 0.01$), suggesting that organizational youth and flexibility enhance the efficacy of AI implementation in financial decision-making processes. The relationship progressively attenuates through the maturity phase ($\beta = 0.002$, $p < 0.10$) and becomes statistically insignificant for firms in decline.

This pattern of declining effectiveness across life cycle stages presents several theoretical and practical implications. From a theoretical perspective, the results suggest that organizational characteristics associated with different developmental stages—such as structural flexibility, resource availability, and strategic orientation—significantly moderate the AI-asset allocation relationship. From a practical standpoint, these findings indicate that firms must calibrate their AI adoption strategies to align with their life cycle position.

Our analysis also identifies critical avenues for future research. Scholars should examine the specific organizational mechanisms that drive the differential effectiveness of AI adoption across life cycle stages. Particular attention should be directed toward understanding the transition points between stages, where the relationship's strength appears to shift most dramatically. Additionally, investigating how firms can maintain AI implementation effectiveness despite life cycle-related constraints represents a promising direction for future inquiry.

## 5. Conclusion and Future Research Directions

This study examines the complex interplay between artificial intelligence adoption and corporate financial asset allocation, emphasizing the distinctive roles of organizational dynamic capabilities. Through comprehensive empirical analysis of extensive panel data from Chinese A-share listed companies spanning 2008-2022, we establish robust evidence that transcends simple correlational relationships. Our methodological approach, incorporating instrumental variable analysis and Heckman selection procedures, addresses potential endogeneity concerns and selection bias, strengthening the causal interpretation of our findings.

Our analyses reveal that AI adoption significantly enhances financial asset allocation efficiency, with this effect persisting across multiple empirical specifications and robustness tests. The relationship between AI implementation and asset allocation outcomes is distinctly shaped by organizational dynamic capabilities. Absorptive capability emerges as the predominant moderating force, followed by innovative and adaptive capabilities. This hierarchy of effects suggests that organizations' ability to recognize, assimilate, and apply new technological knowledge fundamentally determines their success in leveraging AI for financial decision-making.

The life cycle analysis introduces an essential temporal dimension to our understanding. Growing firms demonstrate markedly stronger positive effects from AI adoption compared to their mature counterparts, while declining firms show minimal benefits. This pattern implies that organizational flexibility and adaptability, typically associated with earlier developmental stages, significantly influence firms' capacity to derive value from AI investments.

These insights extend beyond theoretical contributions to offer practical guidance for organizational strategy and policy development. Firms should cultivate absorptive capabilities alongside their AI initiatives, while remaining mindful of their developmental stage when designing implementation strategies. Our findings emphasize the importance of building complementary organizational capabilities to maximize returns on AI investments.

Looking forward, several promising research directions emerge. Scholars might explore alternative instrumental approaches to further strengthen causal inference or develop dynamic models capturing the temporal evolution of AI adoption effects. Cross-national studies could illuminate how institutional environments shape AI effectiveness, while industry-specific analyses might reveal sector-level variations in adoption patterns. Additional research might examine how organizational capabilities evolve in response to AI implementation, potentially revealing recursive relationships between technological adoption and capability development.

This research faces certain boundaries. Our focus on Chinese markets, while providing rich empirical context, suggests opportunities for broader geographical investigation. Future work might explore how varying institutional frameworks influence the AI-asset allocation relationship. Additionally, examining industry-specific factors and organizational characteristics could provide deeper insights into the conditions that optimize AI implementation.

The transformation of financial decision-making through AI technology continues to accelerate. Our findings highlight the critical importance of organizational capabilities in shaping this transformation. As firms navigate this evolving landscape, success will increasingly depend on their ability to develop and leverage these fundamental capabilities. We anticipate that our research will catalyze further investigation into the intersection of technological innovation and corporate financial management, ultimately informing more effective organizational strategies and policies.

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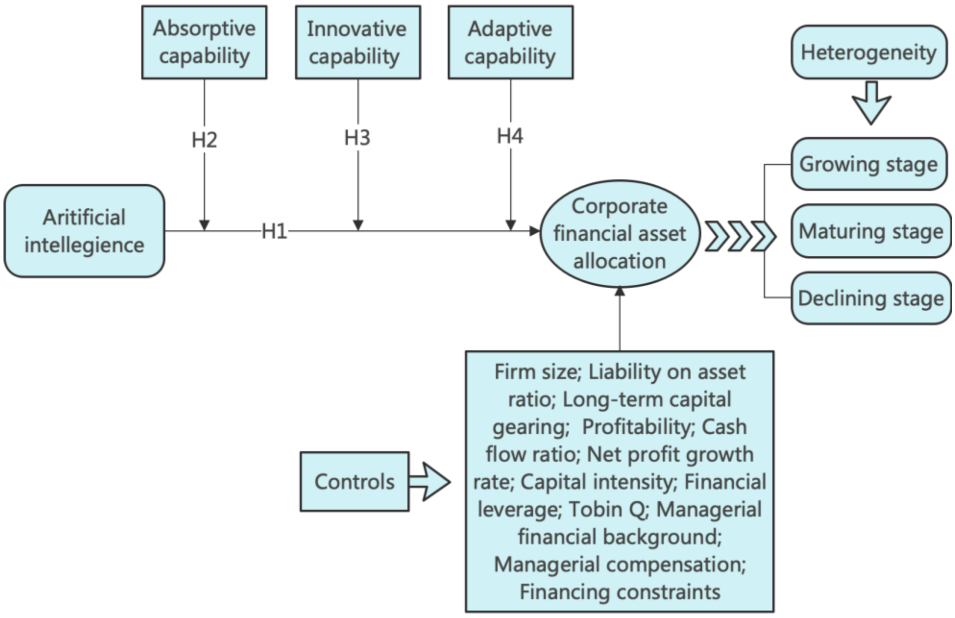


Figure 1. Analytical framework

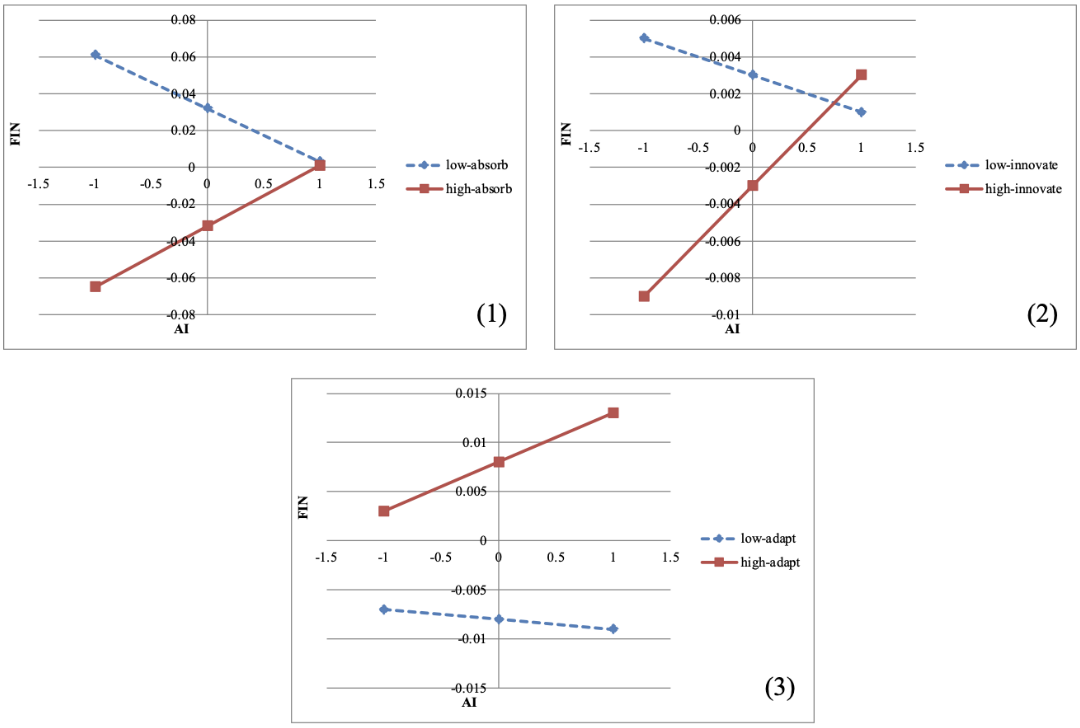


Figure 2. Comparison of the moderating effect of three dynamic capabilities

Table 1. Variable definition

| Variable | | Abbreviation | Measurement |
|---|---|---|---|
| Explained variable | Corporate financial asset allocation | FIN | The calculation method is: (Financial assets for trading + Derivative financial assets + Available-for-sale financial assets + Held-to-maturity investments + Long-term equity investments + Investment properties)/ Total assets. Additionally, we construct a dummy variable (FIN2) of possession of financial asset as an alternative measure, we assign a value of 1 if firm *i* holds financial assets in year *t*, vice versa 0. |
| Explanatory variable | Artificial intelligence adoption | AI | Natural logarithm of the frequency of words related to artificial intelligence in annual reports of listed companies plus one. Besides, we use the natural logarithm of the number of AI patents filed by listed companies in the year plus one as an alternative measure of AI (AI_patent). |
| Moderating variables | Absorptive capability | Absorb | Ratio of the company's annual R&D expenditures to operating revenues |
| | Innovative capability | Innovate | The ratio of R&D investment to operating income and the ratio of technical staff to total employees are used for comprehensive evaluation, and the data of these two indicators are standardized separately and then summed up to get the index of enterprise innovation capacity |
| | Adaptive capability | Adapt | The coefficients of variation of the three major expenditures, namely, R&D expenditures, capital expenditures, and advertising expenditures, are used to reflect the degree of flexibility in the allocation of resources, and thus to measure the adaptive capacity of the firms.Since the results are negative indicators, the results are taken as negative values, and the larger the value, the greater the adaptive capacity of the firms. |
| Control variables | Firm size | Size | Natural logarithm of total assets for the year |
| | Liability on asset ratio | Lev | Total liabilities at the end of the year / Total assets at the end of the year |
| | Long-term capital gearing | DLCR | Non-current liabilities / (Owners' equity + non-current liabilities) |
| | Profitability | ROE | Net profit / average balance of owners' equity |
| | Cash flow ratio | Cashflow | Net cash flows from operating activities / total assets |
| | Net profit growth rate | NetGrowth | Net profit for the year / Net profit for the previous year - 1 |
| | Capital intensity | CAP | Total Assets / Operating Revenue |
| | Financial leverage | FL | (Net Profit + Income Tax Expense + Financial Expense) / (Net Profit + Income Tax Expense) |
| | Tobin Q | TobinQ | (Market value of outstanding shares + number of non-outstanding shares × net assets per share + book value of liabilities) / Total assets |
| | Managerial financial background | FinBack | Whether any of the current directors and supervisors have a financial background (e.g., regulators, banks, securities, futures, investment companies, trusts, etc.) |

| | | |
|---|---|---|
| | | If yes, the value will be 1, otherwise it will be 0. |
| Managerial compensation | Compen | The natural logarithm of total managerial compensation |
| Financing constraints | SA | SA=-0.737*Size+0.043*Size^2-0.040*Age |

Table 2. Descriptive statistics

| Variable | N | Mean | p50 | SD | Min | Max |
|---|---|---|---|---|---|---|
| FIN | 25811 | 0.0450 | 0.00900 | 0.0800 | 0 | 0.452 |
| AI | 25811 | 0.993 | 0.693 | 1.259 | 0 | 4.489 |
| Absorb | 25811 | 0.0540 | 0.0400 | 0.0530 | 0.00100 | 0.342 |
| Innovate | 25811 | 1.135 | 1.157 | 0.533 | 0.0200 | 2 |
| Adapt | 25811 | -0.628 | -0.596 | 0.306 | -1.357 | -0.0820 |
| Size | 25811 | 22.08 | 21.87 | 1.250 | 19.92 | 25.93 |
| Lev | 25811 | 0.376 | 0.365 | 0.189 | 0.0550 | 0.834 |
| Cashflow | 25811 | 0.0510 | 0.0500 | 0.0640 | -0.137 | 0.234 |
| CAP | 25811 | 2.267 | 1.894 | 1.499 | 0.429 | 11.40 |
| FL | 25811 | 1.196 | 1.027 | 0.716 | -0.222 | 5.784 |
| FinBack | 25811 | 0.591 | 1 | 0.492 | 0 | 1 |
| Compen | 25811 | 15.41 | 15.39 | 0.694 | 12.98 | 17.21 |
| SA | 25811 | -3.790 | -3.793 | 0.252 | -4.377 | -3.096 |

Table 3. VIF check

| Variable | VIF | 1/VIF |
|---|---|---|
| Size | 2.160 | 0.463 |
| Lev | 1.800 | 0.554 |
| Absorb | 1.690 | 0.593 |
| Compen | 1.640 | 0.608 |
| CAP | 1.290 | 0.776 |
| Innovate | 1.250 | 0.801 |
| AI | 1.240 | 0.804 |
| Adapt | 1.180 | 0.847 |
| SA | 1.160 | 0.859 |
| Cashflow | 1.150 | 0.869 |

| | | |
|---|---|---|
| FL | 1.150 | 0.871 |
| FinBack | 1.040 | 0.965 |
| Mean | 1.400 | 0.751 |

Table 4. Baseline regression

| VARIABLES | (1)<br>FIN | (2)<br>FIN |
|---|---|---|
| AI | 0.001** | 0.002*** |
| | (2.290) | (3.819) |
| Size | | 0.002*** |
| | | (3.812) |
| Lev | | -0.094*** |
| | | (-27.783) |
| Cashflow | | 0.052*** |
| | | (6.594) |
| CAP | | 0.005*** |
| | | (14.549) |
| FL | | 0.001** |
| | | (2.083) |
| FinBack | | 0.003*** |
| | | (2.711) |
| Compen | | 0.003*** |
| | | (3.694) |
| SA | | -0.007*** |
| | | (-3.220) |
| Constant | 0.025 | -0.094*** |
| | (0.987) | (-3.284) |
| Observations | 25,811 | 25,811 |
| R-squared | 0.148 | 0.196 |
| IND | FE | FE |
| YEAR | FE | FE |

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

Table 5. Endogeneity issues

| VARIABLES | (1) 2SLS | | (2) Heckman |
|---|---|---|---|
| | AI | FIN | FIN |
| L.AI | 0.817*** | | |
| | (191.476) | | |
| AI | | 0.002*** | 0.008*** |
| | | (3.438) | (4.616) |
| Size | 0.007 | 0.002*** | 0.007*** |
| | (1.442) | (3.002) | (4.943) |
| Lev | -0.023 | -0.092*** | -0.125*** |
| | (-0.837) | (-25.100) | (-13.703) |
| Cashflow | -0.101 | 0.055*** | 0.078*** |
| | (-1.536) | (6.183) | (7.380) |
| CAP | -0.002 | 0.005*** | 0.007*** |
| | (-0.856) | (9.736) | (12.191) |
| FL | -0.004 | 0.001* | -0.000 |
| | (-0.697) | (1.848) | (-0.290) |
| FinBack | 0.002 | 0.002** | 0.000 |
| | (0.243) | (2.088) | (0.364) |
| Compen | 0.030*** | 0.002** | 0.013*** |
| | (4.063) | (2.451) | (4.697) |
| SA | 0.029 | -0.007*** | -0.049*** |
| | (1.619) | (-2.679) | (-4.221) |
| imr1 | | | 0.078*** |
| | | | (3.695) |
| Constant | -0.069 | -0.006 | -0.562*** |
| | (-0.241) | (-0.301) | (-4.326) |
| Observations | 21,729 | 21,729 | 25,811 |
| R-squared | 0.816 | 0.189 | 0.196 |
| IND | FE | FE | FE |
| YEAR | FE | FE | FE |

Table 6. Robustness checks

| VARIABLES | (1) Alternative measure of AI FIN | (2) Alternative measure of FIN FIN2 | (3) Alternative model specification FIN | (4) Alternative sample construction FIN |
|---|---|---|---|---|
| AI_patent | 0.001*** | | | |
| | (4.867) | | | |
| AI | | 0.008*** | 0.006*** | 0.010*** |
| | | (2.999) | (14.849) | (2.697) |
| Size | 0.002*** | 0.091*** | 0.000 | 0.115*** |
| | (3.059) | (30.901) | (0.315) | (27.170) |
| Lev | -0.093*** | -0.062*** | -0.082*** | -0.009 |
| | (-27.588) | (-3.566) | (-24.412) | (-0.361) |
| Cashflow | 0.050*** | 0.005 | 0.065*** | -0.016 |
| | (6.380) | (0.123) | (8.190) | (-0.274) |
| CAP | 0.005*** | -0.003* | 0.006*** | -0.004 |
| | (14.855) | (-1.681) | (19.157) | (-1.548) |
| FL | 0.001** | 0.005 | -0.001 | 0.007 |
| | (2.135) | (1.521) | (-0.979) | (1.493) |
| FinBack | 0.003*** | -0.005 | -0.003*** | -0.014** |
| | (2.776) | (-0.928) | (-3.353) | (-1.961) |
| Compen | 0.003*** | 0.000 | 0.014*** | -0.004 |
| | (3.724) | (0.103) | (15.986) | (-0.568) |
| SA | -0.008*** | -0.168*** | -0.039*** | -0.203*** |
| | (-3.572) | (-15.517) | (-20.197) | (-12.850) |
| Constant | -0.088*** | -1.957*** | -0.309*** | -2.484*** |
| | (-3.057) | (-13.337) | (-23.198) | (-14.199) |
| Observations | 25,785 | 25,811 | 25,811 | 15,831 |
| R-squared | 0.196 | 0.246 | 0.097 | 0.256 |
| IND | FE | FE | FE | FE |
| YEAR | FE | FE | FE | FE |

Table 7. The moderating effect of absorptive capability

| VARIABLES | (1)<br>FIN | (2)<br>FIN |
|---|---|---|
| AI | 0.002*** | 0.002*** |
| | (3.807) | (3.036) |
| AI*Absorb | | 0.031*** |
| | | (4.998) |
| Absorb | -0.002 | -0.032** |
| | (-0.171) | (-2.436) |
| Size | 0.002*** | 0.002*** |
| | (3.753) | (3.377) |
| Lev | -0.094*** | -0.093*** |
| | (-27.637) | (-27.482) |
| Cashflow | 0.052*** | 0.053*** |
| | (6.585) | (6.697) |
| CAP | 0.005*** | 0.005*** |
| | (13.772) | (14.164) |
| FL | 0.001** | 0.001* |
| | (2.083) | (1.947) |
| FinBack | 0.003*** | 0.003*** |
| | (2.711) | (2.753) |
| Compen | 0.003*** | 0.004*** |
| | (3.662) | (3.918) |
| SA | -0.007*** | -0.006*** |
| | (-3.195) | (-3.009) |
| Constant | -0.094*** | -0.092*** |
| | (-3.285) | (-3.218) |
| Observations | 25,811 | 25,811 |
| R-squared | 0.196 | 0.197 |
| IND | FE | FE |
| YEAR | FE | FE |

Table 8. The moderating effect of innovative capability

| VARIABLES | (1) | (2) |
|---|---|---|

| | FIN | FIN |
|---|---|---|
| AI | 0.002*** | 0.002*** |
| | (3.889) | (3.017) |
| AI*Innovate | | 0.004*** |
| | | (4.987) |
| Innovate | -0.003*** | -0.003*** |
| | (-2.995) | (-3.018) |
| Size | 0.002*** | 0.002*** |
| | (3.945) | (3.808) |
| Lev | -0.094*** | -0.094*** |
| | (-27.887) | (-27.875) |
| Cashflow | 0.051*** | 0.052*** |
| | (6.553) | (6.634) |
| CAP | 0.005*** | 0.005*** |
| | (14.635) | (14.562) |
| FL | 0.001** | 0.001* |
| | (2.008) | (1.934) |
| FinBack | 0.003*** | 0.003*** |
| | (2.623) | (2.634) |
| Compen | 0.003*** | 0.003*** |
| | (3.718) | (3.745) |
| SA | -0.007*** | -0.007*** |
| | (-3.377) | (-3.264) |
| Constant | -0.095*** | -0.095*** |
| | (-3.341) | (-3.332) |
| Observations | 25,811 | 25,811 |
| R-squared | 0.196 | 0.197 |
| IND | FE | FE |
| YEAR | FE | FE |

Table 9. The moderating effect of adaptive capability

| VARIABLES | (1) | (2) |
|---|---|---|
| | FIN | FIN |

| | | |
|---|---|---|
| AI | 0.002*** | 0.002*** |
| | (3.438) | (2.971) |
| AI*Adapt | | 0.003** |
| | | (2.079) |
| Adapt | 0.008*** | 0.008*** |
| | (4.372) | (4.576) |
| Size | 0.002*** | 0.002*** |
| | (3.993) | (3.969) |
| Lev | -0.093*** | -0.093*** |
| | (-27.542) | (-27.570) |
| Cashflow | 0.054*** | 0.055*** |
| | (6.888) | (6.936) |
| CAP | 0.005*** | 0.005*** |
| | (14.960) | (14.935) |
| FL | 0.001** | 0.001** |
| | (2.093) | (2.106) |
| FinBack | 0.003*** | 0.003*** |
| | (2.800) | (2.818) |
| Compen | 0.003*** | 0.003*** |
| | (3.615) | (3.653) |
| SA | -0.006*** | -0.006*** |
| | (-2.954) | (-2.937) |
| Constant | -0.088*** | -0.088*** |
| | (-3.081) | (-3.073) |
| Observations | 25,811 | 25,811 |
| R-squared | 0.196 | 0.197 |
| IND | FE | FE |
| YEAR | FE | FE |

Table 10. Heterogeneity check

| VARIABLES | Growing stage | Maturing stage | Declining stage |
|---|---|---|---|
| | FIN | FIN | FIN |
| AI | 0.002*** | 0.002* | 0.002 |

| | | | |
|---|---|---|---|
| | (3.230) | (1.891) | (1.190) |
| Size | 0.002** | 0.001 | 0.005*** |
| | (2.365) | (1.274) | (3.343) |
| Lev | -0.090*** | -0.101*** | -0.078*** |
| | (-19.016) | (-16.775) | (-9.100) |
| Cashflow | 0.047*** | 0.084*** | 0.036* |
| | (4.208) | (4.990) | (1.763) |
| CAP | 0.003*** | 0.006*** | 0.007*** |
| | (7.192) | (8.712) | (9.259) |
| FL | 0.001 | 0.003** | -0.000 |
| | (0.793) | (2.376) | (-0.044) |
| FinBack | 0.003** | 0.002 | 0.004 |
| | (2.361) | (0.971) | (1.336) |
| Compen | 0.004*** | 0.003* | 0.002 |
| | (3.664) | (1.799) | (0.902) |
| SA | -0.004 | 0.001 | -0.014** |
| | (-1.573) | (0.158) | (-2.456) |
| Constant | -0.114*** | -0.018 | -0.180* |
| | (-2.837) | (-0.408) | (-1.710) |
| Observations | 12,112 | 9,290 | 4,348 |
| R-squared | 0.186 | 0.218 | 0.204 |
| IND | FE | FE | FE |
| YEAR | FE | FE | FE |