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AI Maturity and Corporate Financial Outcomes: Evidence from Egyptian Listed Firms

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Abstract

This study investigates whether documented corporate artificial-intelligence (AI) maturity is associated with coherent changes in financial decisions, corporate financial performance, financial stability and firm value. It examines a researcher-approved panel of 12 Egyptian listed firms, comprising four banks and eight heterogeneous nonbanks, over 2016–2025. The year 2016 establishes lagged variables, while estimation covers 2017–2025. Inference incorporates firm-clustered standard errors, small-cluster sensitivity procedures and adjustments for multiple testing. The main financial-decision and valuation models provide no robust evidence of a systematic association with AI maturity at the 5% level. Among nonbanks, prior attainment of operational implementation is positively associated with accounting asset turnover ($\beta = 0.09493$; $N = 72$). However, only six firms change attainment status within the estimation sample, and the association does not survive the twelve-comparison Holm adjustment under the independently reproducible restricted Rademacher procedure (adjusted $p = 0.09375$). The corresponding archived score-adjusted Webb result also exceeds 5% after adjustment ($p = 0.05688$), while alternative asset denominators, fiscal-year restrictions and sample-composition tests weaken a confirmatory interpretation. Neither the financial-stability proxies nor current and subsequent relative valuation yield robust family-adjusted evidence. These results suggest that documented technological progress should not be equated with contemporaneous financial gains or automatically capitalized into shareholder value. The study contributes a sector-aware, cross-domain assessment of financial associations across distinct measures of AI maturity in an emerging-market setting. Its findings are observational and do not identify a causal implementation effect, a comprehensive financial-stability effect or an AI-to-valuation transmission mechanism.

Keywords: AI maturity; corporate financial decisions; corporate financial performance; financial stability; firm value.

1. Introduction

The financial significance of artificial intelligence (AI) extends beyond technological adoption to the allocation of corporate resources, the realization of operating returns, and the persistence of firm value. AI can expand the information available to managers, improve forecasting and reshape investment opportunities; however, these capabilities also require complementary intangible capital, organizational adaptation and financing commitments. Whether the benefits exceed these costs, and when they become visible in corporate financial outcomes, therefore remains an important question in

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corporate finance (Babina, Fedyk, He, & Hodson, 2024); (Chen, Kim, & Peng, 2026); (Hsu, Lee, Gong, & Chuang, 2026).

The first channel concerns financial decisions. AI-enabled information processing may help firms screen projects and reduce resource-allocation inefficiencies, as recent evidence on investment efficiency suggests (Chen, Kim, & Peng, 2026); (Hsu, Lee, Gong, & Chuang, 2026); (Lou, Li, & Tong, 2025). At the same time, the financial requirements of technological investment need not decline: AI-investing firms may retain more liquidity and rely on internal funds or equity, while other evidence associates AI investment with tighter financing constraints (Damle & Sinha, 2025); (Yu & Cong, 2026). The financial consequences of AI maturity therefore depend not only on the quality of decisions but also on the nature and funding of the assets being acquired.

A second channel concerns corporate financial performance. Firm-level AI investment has been associated with sales expansion, employment growth and product innovation, while adoption studies report productivity gains conditional on organizational capabilities and the nature of implementation (Babina, Fedyk, He, & Hodson, 2024); (Czarnitzki, Fernández, & Rammer, 2023); (Park, Kang, Yi, & Kim, 2026). Yet operational expansion does not necessarily translate into higher profitability or more intensive utilization of existing assets. Implementation expenditure, the time required to reorganize processes, and differences between technological readiness and actual operating use may generate uneven financial outcomes (Guettoufi, 2026); (McElheran, et al., 2024).

The third financial domain concerns selected indicators of financial downside and relative firm value. We operationalize one narrow aspect of financial stability through the observed magnitude of adverse annual changes in ROA and CFO/assets; these indicators do not jointly measure comprehensive stability, distress avoidance, earnings volatility or resistance to an identified shock. Relative valuation is measured with an annual market-to-book multiple, not realized, dividend-adjusted shareholder return. AI may affect monitoring, planning and risk response, but market prices may also capture expectations or the credibility of disclosures. Evidence on crisis-window outcomes and on the co-occurrence of valuation gains and downside risk is consequently relevant as conceptual context, not as an identical estimand (El Moujahid, Murtinu, & Sekerci, 2026); (Bai, Zhao, & Liu, 2026).

These relationships are further conditioned by the meaning of AI activity itself. Specialist hiring, managerial references, patents, reported operating deployment and technological exposure describe different points along the development of organizational capabilities. Evidence based on such measures cannot automatically be assumed to identify the same economic process or the same valuation horizon (Babina, Fedyk, He, & Hodson, 2024); (Chen, Kim, & Peng, 2026); (Eisfeldt, Schubert, Zhang, & Taska, 2026). A financial assessment of AI consequently requires attention to the timing of documented capability, the sectoral interpretation of balance-sheet measures and the distinction between current operating results and subsequently observed value.

Egypt provides a relevant setting in which to examine these financial relationships. The second National Artificial Intelligence Strategy (2025–2030) identifies the expansion of AI capabilities and their productive application as national priorities, while the Financial Regulatory Authority has established a framework for technological applications in nonbank financial services (National Council for Artificial Intelligence, 2025); (Financial Regulatory Authority, 2026). Research on

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Egyptian banks has already reported heterogeneous links between AI-related measures, profitability and financial stability (Khalil & Abdelraouf, 2026). The importance of the present study lies in examining financial decisions, firm performance, financial stability and firm value within one longitudinal framework for a selected group of Egyptian listed companies. By distinguishing documented stages of AI maturity and respecting sector-specific economic meanings, the analysis seeks to clarify where financial benefits can be observed, how consistently they appear, and where the available evidence remains insufficient; it does not presume that technological advancement necessarily creates shareholder value.

2. Literature Review

Artificial intelligence can reshape corporate finance through more than one route. By altering information processing and the scope of feasible projects, it may affect investment choices and operating outcomes; by changing funding requirements, uncertainty and investors' expectations, it can also influence balance-sheet policies and market valuation. These channels need not move together. The emerging finance literature reports benefits from innovation and decision quality alongside adjustment costs, financing frictions and valuation risks (Babina, Fedyk, He, & Hodson, 2024); (Damle & Sinha, 2025); (Yu & Cong, 2026); (Bai, Zhao, & Liu, 2026). This tension provides a natural basis for examining financial decisions, corporate financial performance, and the stability and valuation of the returns associated with AI.

2.1. AI Maturity and Corporate Financial Decisions

Investment choice and capital allocation

Research on corporate investment has moved beyond asking whether firms invest in AI to examining whether AI-related capabilities alter the quality of investment selection. Analyses of U.S. earnings-call language, 10-K accounts of operational exploitation, and Chinese patent or annual-report evidence generally report higher investment efficiency, often through better forecasting, transparency, internal control and reduced overinvestment (Chen, Kim, & Peng, 2026); (Hsu, Lee, Gong, & Chuang, 2026); (Lou, Li, & Tong, 2025); (Lin, Li, Geng, Yao, & Liu, 2026). Quasi-experimental evidence based on Chinese AI pilot zones similarly links AI development to improved investment efficiency through software investment and reduced agency or financing frictions (Li, Liao, & Tang, 2026). These papers test both the quality of allocation and the information environment in which managers choose projects, rather than merely establishing that reported expenditure increases.

The broader resource-allocation evidence also connects adoption to financial portfolio choices. (Li, Zhong, & Tong, 2024) document greater financial-asset allocation efficiency, conditional on absorptive and other dynamic capabilities; (Deng & Qin, 2026) find higher financial-asset holdings and identify profitability as a more influential channel than alleviated financing constraints. Labor-allocation studies, including (Fu, Zhang, Sun, Liu, & Lu, 2026), add evidence that AI-related changes can curb both excess and insufficient employment investment. Across these contributions, the apparent benefits are contingent on capabilities, organizational context and the particular asset class being reallocated.

Financing, liquidity and funding constraints

A less uniform picture emerges when AI-related commitments are examined from the liability and liquidity sides. (Liu & Hu, 2025) associate AI strategies with improved investment efficiency

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partly through supply-chain finance, while (Damle & Sinha, 2025) find that U.S. firms investing in AI hold more cash and rely relatively more on internal cash generation and equity issuance than on debt. Their evidence is consistent with precautionary reserves and option value accompanying uncertain intangible investments. By contrast, (Yu & Cong, 2026) report that more intensive AI investment is associated with tighter financing constraints, particularly among private firms. (Zhang, Wang, & Yin, 2026) find that intellectual-property protection can improve the financing consequences of AI-related investment and that initial financing pressure may ease at scale. Thus, reduced information frictions and increased short-run financial pressure are plausible, competing financial responses, not interchangeable signs of a single financing effect.

The sectoral meaning of allocation is equally important: bank lending and securities holdings describe the composition of earning assets, whereas nonfinancial or nonbank borrowing describes a source of funds. Studies of corporate financial asset allocation and financialization (Li, Zhong, & Tong, 2024); (Deng & Qin, 2026) show why common language about “resource allocation” can conceal different balance-sheet decisions.

Taken together, the evidence is more consistent in linking AI with improved investment-decision quality than in identifying a common direction for cash reserves, external funding or balance-sheet restructuring. The aggregate pattern therefore depends on the financing margin and on which type of corporate resource is being allocated.

2.2. AI Maturity and Corporate Financial Performance

Growth, profitability and realized output

A first group of studies examines whether the expansion of firm-level AI capabilities is reflected in observable business outcomes. (Babina, Fedyk, He, & Hodson, 2024) associate AI-skilled employment investment with subsequent sales, employment and valuation growth, attributing much of the expansion to new product innovation. Firm-level output studies likewise find that AI-related activity can contribute to output expansion, but the gains are unequal across enterprises and their competitive positions (Sun & Huang, 2026). Evidence on profitability is more heterogeneous. In a sample of Algerian firms, (Guettoufi, 2026) finds that initially favorable profitability differences among adopters become largely insignificant after accounting for firm-specific characteristics, while fixed-asset turnover is lower. These results distinguish observed adoption-associated growth from a generalizable improvement across all measures of financial performance.

Productivity, organizational complements and the adoption margin

At the firm level, survey-based adoption and intensity measures are positively associated with productivity in German enterprises (Czarnitzki, Fernández, & Rammer, 2023), while research on Chinese service companies and broader listed-firm panels reports gains in total factor productivity, often linked to R&D, human capital and financial innovation (Wu & Zhu, 2025); (Jian, Lu, Yang, & Zhong, 2026); (Fan, Liao, & Yang, 2025). Using U.S. AI-skilled hiring and investment signals, (Park, Kang, Yi, & Kim, 2026) identify sectorally uneven TFP gains and find that potential occupational exposure alone does not systematically predict their magnitude. At the task level, (Brynjolfsson, Li, & Raymond, 2025) report a 15% increase in customer-support issues resolved per hour following assistant availability, with much greater benefits for less experienced workers. These results support a

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complements-and-learning account, but also show that output per task, firm-level productivity and corporate financial results arise at different levels of aggregation.

Adoption patterns themselves are heterogeneous. (McElheran, et al., 2024) document substantial dispersion in U.S. firm adoption, and the productivity evidence indicates that implementation purpose and the existing stock of human and organizational capabilities influence realized gains (Czarnitzki, Fernández, & Rammer, 2023); (Park, Kang, Yi, & Kim, 2026). Rather than implying that every additional declaration of AI capability has the same payoff, this research points to possible nonlinearity between technical preparation, operational use and observable business outcomes.

Banking performance and heterogeneity in financial outcomes

Banking studies reinforce the need to examine profitability jointly with cost and risk outcomes. (Li Z. , 2026), using AI-related annual-report and patent indicators for Chinese banks, finds higher bank profitability through cost savings, income diversification and mobile banking. In Egypt, (Khalil & Abdelraouf, 2026) document different signs across ROE, net interest margin and asset utility, with financial stability conditioning some profitability associations. A broader Asia-Pacific analysis by (Le & Wu, 2026) finds that adopters initially exhibit a more favorable joint return–risk configuration, which can deteriorate over time. These results caution against treating profitability and the persistence of financial benefits as identical phenomena.

Overall, studies frequently associate AI capabilities and adoption with stronger output, growth or productivity, especially where complementary organizational capabilities are present. Evidence of broad, persistent improvements in corporate financial performance is less uniform, and its direction varies with the sector, observation horizon and form of technological application.

2.3. AI Maturity, Financial Stability, and Firm Value

AI capabilities, firm value and the credibility of corporate disclosures

A growing corporate-finance literature asks how investors capitalize expected benefits from AI. (Babina, Fedyk, He, & Hodson, 2024) link identifiable firm-level AI investment to greater valuations alongside product-led growth; (Chen, Kim, & Peng, 2026) additionally document higher longer-horizon Tobin's q for firms with stronger managerial AI references. Studies of data assets and managerial capacity, and of AI-related technology and narrative signals, associate complementary organizational resources with higher enterprise value (Shi, Wu, Qin, & Liu, 2025); (Xing, Zhang, & He, 2026). (Eisfeldt, Schubert, Zhang, & Taska, 2026) investigate a different valuation object—the market repricing of firms with varying workforce exposure to generative AI around the technology shock—rather than treating all AI mentions as verified deployment. Together, these results indicate that investors may price anticipated gains as well as demonstrated capabilities, with distinct timing across the two.

The credibility of disclosed AI activity complicates this valuation channel. (Basnet, Elias, Salganik-Shoshan, Walker, & Zhao, 2025) distinguish substantive from speculative corporate AI narratives and find more favorable reactions to actionable disclosures. Studies of AI washing reach less reassuring conclusions: (Li Z. , 2026) associate disclosure–investment gaps with greater crash risk, whereas (Yang, 2026) identifies a nonlinear relation in which limited narrative inflation can coincide with valuation gains before excessive exaggeration becomes detrimental. (Bai, Zhao, & Liu, 2026), in a pre-registered study of a Chinese AI policy setting, find increased crash risk alongside

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higher firm value, linking the joint pattern to optimism and opacity. Market appreciation can therefore coexist with greater left-tail risk; a higher price alone is not sufficient evidence of a more stable payoff.

Financial stability, performance variability and resilience

The literature examines financial stability through several related but distinct outcomes, including earnings and financing conditions, return variability, default exposure, risk management and the ability to maintain performance during adverse shocks. Studies report that AI innovation may reduce subsequent stock-price crash risk through improved information and internal oversight (J. (Zhang, Cui, Zheng, & Taylor, 2025), while corporate adoption has been associated with lower financial risk and debt-default exposure (Liu, Gao, & Chen, 2025); (Dong, Wang, & Lian, 2026). (Chen, Liu, Chen, Wang, & Zhang, 2026) document multidimensional corporate resilience, encompassing resistance, recovery and financing stability. Using a distinct crisis-period design, (El Moujahid, Murtinu, & Sekerci, 2026) find stronger stock returns and lower volatility among firms that adopted AI before the COVID-19 shock, alongside evidence from operating performance and valuation. These studies do not imply that the stability measures they employ are interchangeable.

However, the stability and valuation evidence remains heterogeneous across horizons and sectors. (Le & Wu, 2026) report that an initially favorable return–risk balance in banks may deteriorate as follow-up lengthens, whereas (Bai, Zhao, & Liu, 2026); (Li Z. , 2026) emphasize the roles of managerial optimism, disclosure credibility and unsubstantiated AI claims in market risk. Consequently, a higher market valuation, a smoother operating outcome and stronger resilience to external shocks need not coexist.

In aggregate, the literature associates some AI activities with stronger firm value, improved risk management and greater financial resilience, but these results depend on the authenticity of deployment, disclosure quality, institutional context and observation horizon. The overarching direction is therefore heterogeneous rather than uniformly favorable: financial stability and firm value are connected economic outcomes, not equivalent constructs.

3. Research Gap

Although studies increasingly link AI-related activities to investment efficiency, growth, market valuation and risk, evidence across these financial domains is not readily comparable. Measures based on managerial language, hiring, patents, documented implementation or potential exposure capture different organizational phenomena (Babina, 2026), while studies examine different outcomes and time horizons. Consequently, a favorable association in one domain cannot establish that other dimensions of corporate finance improve alongside it.

A more specific finance question is whether successive stages of documented AI maturity exhibit a coherent relationship with investment and financing decisions, accounting performance, financial stability and market value when sector-specific meanings of these outcomes are respected. Existing evidence is mixed across institutional settings and banking studies (Guettoufi, 2026); (Khalil & Abdelraouf, 2026); (Le & Wu, 2026). The literature does not thereby establish a common, stage-dependent pattern across all four financial constructs.

This study addresses that comparability problem through a common firm-level chronology and distinct documentary representations of AI maturity. Its contribution is an integrated assessment of

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where conditional financial associations appear, where they remain inconclusive, and how their interpretation changes across financial constructs and sectors. Rather than assuming a sequential investment–performance–valuation mechanism, it examines whether the observed evidence is consistent with such a narrative.

4. Research Questions

Central research question. Across which financial domains and stages of documented AI maturity do differences in corporate financial decisions, financial performance, financial stability and firm value become observable, and how coherent are these patterns over time?

Financial decisions. How do investment commitments, financing choices and sector-specific balance-sheet allocations vary across documented stages of AI maturity, and where do their observed patterns converge or diverge?

Corporate financial performance. At which stages of AI maturity do differences in asset utilization, profitability and business growth emerge, and how consistent are these differences across operational and measurement contexts?

Financial stability and firm value. How do the stability and variability of financial performance, together with current and subsequent firm value, differ across documented stages of AI maturity, and what can the observed horizon establish about the persistence of those patterns?

5. Research hypotheses and their financial domains

5.1. AI maturity and corporate financial decisions

H1. Documented AI maturity is associated with corporate financial decisions across (H1a) intangible investment intensity, (H1b) nonbank capital expenditure, and (H1c) economically distinct nonbank financing and bank balance-sheet allocation measures.

5.2. AI maturity and corporate financial performance

H2. Documented AI maturity is associated with multidimensional corporate financial performance through (H2a) asset utilization, (H2b) profitability and (H2c) business growth. CFO/assets is a supplementary performance indicator. The continuous maturity measure and prior attainment of operational stage 4–5 are alternative explanatory exposures; implementation duration, asset-denominator definitions and firm-specific trends are specification checks, not separate conceptual hypotheses.

5.3. AI maturity, financial stability, and firm value

H3. Documented AI maturity is associated with financial stability and firm value through (H3a) observed adverse annual changes in financial performance, as one measurable aspect of stability, (H3b) direct relative firm value, (H3c) the conditional value relevance of resource allocation, and (H3d) subsequent relative firm value and adverse changes in its valuation multiple. The observed indicators do not equate stability to the absence of decline or identify shock resilience or distress avoidance.

The hypotheses examine related financial domains, not a causal mediation chain. Threshold, duration, downside and forward-valuation estimates are exploratory extensions, and their evidence is evaluated with the stated multiplicity and specification limits.

6. Data and measurement

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6.1. Selected cohort and coverage

The approved panel comprises 120 firm-year observations for 12 Egyptian listed firms in 2016–2025. The year 2016 is used to construct lagged exposures and controls; models are estimated over 2017–2025, with outcome-specific estimation samples. The cohort includes four banks (ADIB, CIB, CIEB and QNBA) and eight heterogeneous nonbanks. Bank asset-allocation ratios and nonbank borrowing are analyzed separately because they represent different financial decisions. The nonbank accounting-performance sample includes observations preceding some firms' listings; listed-only estimates are assessed as a robustness check. Fiscal years end in June for ALCN, August for TALM and December for the other firms; year effects therefore refer to fiscal-year labels.

6.2. Evidence-based AI maturity

Table 1. Evidence-based annual AI maturity rubric

Stage	Documentary interpretation
0	No qualifying evidence in the reviewed source period
1	Awareness
2	Discussion or planning
3	Institutional capability or investment
4	Documented operational implementation
5	Strategic integration

Let A_{it} denote the approved annual documentary grade (0–5), $S_{it} = \max(A_{i,2016}, \ldots, A_{it})$ the highest previously documented stage, $M_{i,t-1} = S_{i,t-1}/5$ its lagged normalized value, and $D_{i,t-1} = 1[S_{i,t-1} \geq 4]$ prior attainment of operational stage 4 or 5. Historical attainment records a documented milestone, not continuous subsequent deployment. Duration models use years since first attainment, lagged to the outcome year; specifications involving log turnover transform the outcome, not duration.

6.3. Financial decisions, corporate financial performance, financial stability and firm value

Table 2. Construct operationalization and domain limits

Construct	Operational measure	Applicability
Intangible investment	Annual recognized intangible additions / current total assets	Pooled twelve-firm and nonbank sensitivity; not AI-only expenditure
Tangible investment	Approved capital expenditure / current total assets	Eight nonbanks; scale rather than investment efficiency
Financing and balance-sheet allocation	Nonbank debt/assets; bank loans/assets and investment securities/assets	Bank loan assets are not interchangeable with nonbank corporate borrowing
Asset utilization	Revenue/current total assets; beginning- and average-asset alternatives	Eight nonbanks; a flow/stock ratio, not total factor productivity

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Construct	Operational measure	Applicability
Financial performance	ROA = net income / assets; CFO/assets; revenue growth	Separate operating dimensions; no bank/nonbank turnover pooling
Annual financial downside	max(ROA_(t−1) − ROA_t, 0); max(CFO/assets_(t−1) − CFO/assets_t, 0)	Observed adverse annual change, not exogenous-shock resilience
Firm value	M/B = market capitalization / parent book equity	Listed observations only; affected by book-equity denominator
Valuation downside and lead	max(M/B_(t−1) − M/B_t, 0); ΔM/B_(t+1) = M/B_(t+1) − M/B_t	Not inflation- or dividend-adjusted real shareholder wealth
Controls	Lagged ln assets, ROA, cash/assets and debt/assets; exact model specification retained	Control sets can differ by original focal family; no silent common-case sample

7. Econometric methodology

7.1. Model specifications

The benchmark firm and fiscal-year-label fixed-effects specification is $Y_{it} = \alpha_i + \lambda_t + \beta M_{i,t-1} + \gamma' X_{i,t-1} + \varepsilon_{it}$, where M denotes lagged normalized attained maturity and X the recorded lagged controls. The operational-stage specification replaces M with $D_{i,t-1}$. Fiscal-year labels accommodate the approved panel structure but do not imply identical calendar cutoff dates. Lags establish temporal ordering, not exogenous identification.

Financial-decision models estimate intangible additions, nonbank CAPEX and sector-appropriate financing or bank asset allocation separately. Nonbank performance outcomes include asset turnover, ROA and revenue growth, with CFO/assets supplementary. Benchmark controls comprise lagged ln assets, ROA, cash/assets and debt/assets, with debt/assets omitted where financing or bank asset allocation is itself the outcome. Firm value is modeled directly and conditionally on lagged resource allocation. For moderation, $M/B_{it} = \alpha_i + \lambda_t + \beta 1\, M_{i,t-1} + \beta 2\, \text{Allocation}_{i,t-1} + \beta 3(M_{i,t-1} \times \text{Allocation}_{i,t-1}) + \gamma' X_{i,t-1} + \varepsilon_{it}$. The temporal extension includes the relevant lower-order interactions with linear calendar time; it does not use the annual documentary grade as the time interaction.

Exploratory financial-stability models use the positive part of an annual decrease in ROA or CFO/assets, under firm and fiscal-year-label effects and the specified lagged controls. Six focused comparisons cover these outcomes across pooled and nonbank samples and two maturity measures. A separate six-model family evaluates valuation declines and subsequent-year changes in M/B. Forward-change specifications condition on current M/B; matched turnover–subsequent-valuation models instead use subsequent M/B in levels. Detailed model lists, complete-case samples and replication protocols are supplied in the statistical supplement.

7.2. Inference with few clusters and multiplicity adjustment

Firm-clustered CR1 is reported alongside CR2–Satterthwaite references where available; these methods accommodate within-firm dependence but do not generally remove dependence across firms. Because cluster counts are small (12 overall, eight nonbanks and four banks), the independent

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primary reference for the exploratory operational-threshold test is restricted-null wild-cluster Rademacher (WCR-C), with exhaustive enumeration of 2^G firm sign patterns. Exhaustive enumeration is exact for the chosen sign set conditional on its assumptions, not a guarantee of exact finite-sample inference (Arellano, 1987); (Cameron & Miller, 2025); (Pustejovsky & Tipton, 2018); (MacKinnon & Webb, 2018).

Multiplicity is addressed using Holm's step-down procedure within clearly identified comparison families (Holm, 1979). The financial-stability and forward-valuation extensions each have a distinct six-comparison family. The principal operational-threshold inference uses the twelve-measurement comparison family, with broader and narrower post hoc families presented as sensitivity analyses rather than as alternative routes to significance. Archived score-adjusted Webb (WCR-S) results are retained for procedure comparison; their Holm arithmetic was verified independently, but the original score-adjusted bootstrap algorithm was not rerun.

7.3. Specification and diagnostic checks

Robustness analyses vary the asset-turnover denominator, AI representation, firm-specific trends, estimation period, listed-only restriction, lag timing, firm composition and exposure to specified group-by-year shocks. Diagnostics examine heteroskedasticity, serial and cross-sectional dependence; Mundlak specifications assess correlated firm effects (Mundlak, 1978); (Koenker, 1981); (Pesaran, 2004). These checks qualify model interpretation rather than establishing causal identification.

Timing sensitivity includes December-year-end nonbanks, deletion of individual outcome years and matched comparisons of one- and two-year lags with the benchmark controls held at t−1. Composition sensitivity includes joint exclusion of EFIG, FWRY and HRHO and interactions for that financial/payments-related subset; a bank-by-year interaction is tested in the pooled intangible-investment model. Results and model-specific samples are reported in Section 10 and Appendix A.

8. Descriptive statistics and support

Table 3. Estimation-period descriptive statistics (2017–2025; variable-specific N)

Variable	N	Mean	SD	Median	Min	Max
AI_EXPOSURE	108	0.5037	0.3653	0.6000	0.0000	1.0000
Annual_AI_EXPOSURE	108	0.4630	0.3593	0.6000	0.0000	1.0000
AI_L1	108	0.4167	0.3690	0.4000	0.0000	1.0000
Intangible_Assets	104	0.0084	0.0204	0.0009	0.0000	0.1751
CAPEX_Assets	108	0.0472	0.0636	0.0143	0.0003	0.3839
MarketToBook	98	2.7790	3.8191	1.4473	0.3477	30.9374
SIZE_L1	108	10.1487	1.9970	10.4909	5.0106	14.0102
ROA_L1	108	0.0826	0.1125	0.0420	-0.0506	0.5334
Cash_Assets_L1	108	0.2030	0.1681	0.1474	0.0100	0.7072

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Variable	N	Mean	SD	Median	Min	Max
Debt_Assets_L1	108	0.1330	0.1672	0.0407	0.0000	0.5917
Retained_Assets	108	0.0935	0.1054	0.0624	-0.0564	0.5480

Note. Statistics cover 2017–2025 with variable-specific observations. AI_EXPOSURE denotes current historically attained stage/5; Annual_AI_EXPOSURE denotes annual evidence grade/5; AI_L1 denotes lagged attained stage/5. CAPEX descriptives include all firms; CAPEX regressions use nonbanks.

Table 3 presents the distribution and dispersion of the principal financial and AI-maturity measures used in the empirical analysis. Differences in coverage across variables should be considered when comparing their descriptive patterns.

Table 4. Equal-firm means across two descriptive five-year windows

Cohort	Measure	Firms	P1 mean	P2 mean	Sign-flip p	Holm-adjusted p
All 12	AI	12	1.1000	3.4667	—	—
Nonbank 8	Turnover	8	0.6060	0.5274	0.04688	0.46875
Nonbank 8	ROA	8	0.1005	0.1245	0.07031	0.56250
Nonbank 8	CFO_Assets	8	0.1116	0.1168	0.71875	1.00000
Bank 4	AI	4	1.5500	3.3500	—	—
Bank 4	Bank loans/assets	4	0.4300	0.4028	0.37500	Not in this Holm family
Bank 4	Bank securities/assets	4	0.2543	0.2525	0.87500	Not in this Holm family

Note. The two descriptive windows are 2016–2020 and 2021–2025; 2016 is excluded from the regression window. Historical highest attainment is mechanically nondecreasing by construction; the comparison is descriptive.

The mean historical attained-stage code rose from 1.10 to 3.47 across twelve equally weighted firms, a descriptive consequence of additional recorded attainments and a nondecreasing coding convention—not independent evidence of uninterrupted deployment. Nonbank mean turnover fell from 0.6060 to 0.5274 between windows without covariate adjustment. Neither comparison establishes nor negates the conditional threshold coefficient.

Table 5. Company-specific maturity trajectories and first advanced-attainment year

Firm	2020 stage	2025 stage	Δ	Mean stage P1	Mean stage P2	First 4–5
ADIB	0	4	4	0.00	1.20	2025
ALCN	2	5	3	0.40	4.20	2021
CIB	4	5	1	2.80	4.20	2019
CIEB	4	4	0	2.60	4.00	2019
EFIG	3	4	1	1.20	3.80	2022

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Firm	2020 stage	2025 stage	Δ	Mean stage P1	Mean stage P2	First 4–5
ETEL	4	4	0	2.40	4.00	2018
FWRY	0	4	4	0.00	3.20	2025
GBCO	0	4	4	0.00	3.20	2023
HRHO	4	5	1	1.60	4.80	2019
QNBA	4	4	0	0.80	4.00	2020
RAYA	3	5	2	1.40	4.00	2022
TALM	0	1	1	0.00	1.00	—

Note. The first-attainment year records the first documented stage 4–5; it does not imply uninterrupted subsequent deployment.

9. Empirical results

The regression tables report conditional estimates and their model-specific inference. Interpretation distinguishes nominal significance from family-adjusted evidence and considers the economic scale and precision of estimates.

9.1. AI maturity and corporate financial decisions

Table 6. Investment, financing and bank asset allocation results

Decision domain	Model / focal outcome	N/G	β	CR1 SE	CR1 p	Wild p
Investment	Pooled intangible additions	104/12	-0.0185	0.0127	0.1736	0.1807
Investment	Nonbank CAPEX	72/8	-0.0744	0.0705	0.3265	0.3281
Investment	Nonbank intangible additions	68/8	-0.0287	0.0196	0.1878	0.2578
Investment	Intangibles, excluding ETEL	95/11	-0.0078	0.0076	0.3303	0.3955
Financing	Nonbank financing debt	72/8	-0.0446	0.0439	0.3429	0.3594
Bank asset allocation	Bank investment securities	36/4	0.0395	0.0711	0.6176	0.8750
Bank asset allocation	Bank loan allocation	36/4	-0.0987	0.0578	0.1862	0.5000

Note. N/G denotes observations/company clusters. β is the lagged cumulative-maturity association; p-values are from the stated CR1 and restricted wild procedures.

The pooled intangible-additions estimate is −0.01848 (N=104, G=12; restricted wild p=0.1807). Nonbank CAPEX/assets has coefficient −0.07435 (N=72, G=8; p=0.3281); nonbank debt/assets gives −0.0446 (p=0.3594). Four-bank securities/assets and loans/assets have respective p-values 0.8750 and 0.5000 under their specified restricted wild procedures. None provides robust 5% support, and the financing estimands are economically sector-specific. The tested H1 indicators provide no robust 5% evidence; no joint omnibus test of the grouped hypothesis is reported.

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The estimated investment and financing coefficients concern aggregate investment intensity and sector-specific balance-sheet shares, not identifiable AI expenditure, investment efficiency or financing constraints. Their imprecision precludes a directional conclusion.

9.2. AI maturity and corporate financial performance

Table 7. Normalized maturity and nonbank performance-level outcomes

Outcome	N/G	Maturity β	CR1 p	Wild p	Jackknife p
Asset_Turnover	72/8	0.0277	0.5917	0.4609	0.6196
CFO_Assets	72/8	-0.0900	0.0991	0.0469	0.0956
Revenue_Growth	72/8	0.2008	0.0972	0.1250	0.1709
ROA	72/8	0.0179	0.7037	0.6953	0.7176
Asset_Turnover_Lead1	64/8	-0.0024	0.9636	0.9453	0.9651
CFO_Assets_Lead1	64/8	-0.1569	0.1091	0.0391	0.1382

Note. β is for lagged cumulative maturity normalized to [0,1]. Jackknife p summarizes company-deletion sensitivity.

Lagged normalized attained maturity is not robustly related to nonbank asset turnover (β=+0.0277; wild p=0.4609), profitability or revenue growth. The negative CFO/assets-level (β=−0.08995) and one-year-forward CFO (β=−0.1569) estimates have nominal wild p-values of 0.0469 and 0.0391, but the corresponding leave-one-firm-out jackknife values are 0.0956 and 0.1382; neither is treated as a robust discovery. Prior attainment of stage 4–5 gives β=+0.09493 for revenue/ending assets (N=72, G=8; independent exact Rademacher p=0.00781, Holm-12=0.09375; archived WCR-S Webb nominal p=0.00474, Holm-12=0.05688). This is a positive, specification-sensitive asset-utilization signal, not evidence of a general efficiency effect.

For the operational-attainment turnover estimate, the registry gives a nominal CR1 95% interval of [0.01998, 0.16989] in revenue/assets units. A coefficient of 0.09493 denotes 0.09493 additional units of revenue per unit of assets, rather than a 9.493% proportional increase. Independent CR2 calculations for this specification give SE=0.03050, Satterthwaite df=5.74 and nominal p=0.02205. These nominal intervals and tests do not account for the full set of explored specifications.

Table 8. Matched nonbank asset-denominator sensitivity (N=72, G=8)

Outcome (N=72; G=8)	Threshold β	CR1 SE	CR1 p	Webb p*	Holm-7*
Revenue / ending assets	+0.09493	0.03170	0.02009	0.00474	0.03318
Revenue / beginning assets	+0.06942	0.07055	0.35785	0.39185	1.00000
Revenue / mean assets	+0.07559	0.02849	0.03279	0.02091	0.12546
ln(revenue / ending assets)	+0.13341	0.13401	0.35264	0.41860	1.00000
ln(revenue / beginning assets)	−0.01597	0.10109	0.87893	0.88173	1.00000
Beginning − ending ratio	−0.02551	0.07320	0.73772	0.70890	1.00000

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Outcome (N=72; G=8)	Threshold β	CR1 SE	CR1 p	Webb p*	Holm-7*
Assets(t)/Assets(t−1) − 1	−0.11007	0.32035	0.74125	0.70667	1.00000

Note. Seven denominator/outcome definitions use the same 72 nonbank observations; * denotes archived score-adjusted WCR-S Webb and independently checked Holm-7 for this diagnostic family. These archived comparisons do not replace the primary WCR-C Rademacher threshold benchmark.

Beginning-asset turnover gives β=+0.06942, archived WCR-S Webb p=0.39185; average-asset turnover gives β=+0.07559, archived WCR-S Webb p=0.02091 but denominator-family Holm p=0.12546. The explicit denominator-gap contrast is not significant (archived WCR-S Webb p=0.70890). Differing nominal significance alone cannot prove a statistically significant contrast between coefficient definitions. In a company-trend sensitivity, the stage coefficient remains positive (β=0.08687; archived WCR-S Webb p=0.02124); duration models are evaluated separately. Neither exercise identifies a causal treatment.

Table 9. Implementation-duration models and specification sensitivity

Duration model	β	SE	WCR-S Webb	Holm-7
Duration + attainment + maturity	0.0443	0.0110	0.04946	0.25152
Same model with company trends	0.0507	0.0292	0.06715	0.25152
Duration + grouped stages	0.0433	0.0141	0.04192	0.25152
Duration + attainment with trends	0.0608	0.0226	0.04955	0.25152
Log-turnover outcome + duration	0.0865	0.0205	0.00364	0.02548
Beginning-turnover outcome + duration	0.0154	0.0148	0.32509	0.65018
Log-turnover outcome + duration and trends	0.0313	0.0846	0.63684	0.65018

Note. Holm adjustment covers the seven duration specifications, not independent replications. All models use N=72 and G=8; duration is linear. The grouped-stage model replaces continuous maturity and the attainment dummy with the reported stage indicators. The Webb p-values are archived WCR-S comparisons; Holm-7 arithmetic was independently checked.

The duration specification with log turnover as the dependent variable has β=+0.08653 and a archived WCR-S Webb seven-model Holm p=0.02548, but the company-trend variant has β=+0.03132 and archived WCR-S Webb p=0.63684. Consequently, no stable independent learning-duration channel is established. H2 receives qualified, dimension-specific exploratory evidence only; it is not labelled confirmatorily or partially supported.

Additional matched-lag and group-shock comparisons are presented in Appendix A3. Their positive coefficients do not establish that the documentary indicator was observable at every fiscal cutoff or that group-specific shocks have been eliminated.

The primary twelve-comparison family does not support the operational-threshold association at 5% under either the independently replicated Rademacher reference or the archived score-adjusted Webb comparator (Table 16).

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9.3. AI maturity, financial stability, and firm value

Table 10. Direct and additive market-to-book regressions

Family	Focal regressor in M/B model	N/G	β	CR1 SE	CR1 p	Wild p
H3	Direct AI–M/B association	98/12	-2.6201	2.3691	0.2924	0.3921
H3	Lagged intangible additions/assets	97/12	-2.3668	12.1247	0.8488	0.8901
H3	Lagged nonbank CAPEX/assets	62/8	6.8303	7.2760	0.3791	0.3594
H3	Lagged nonbank debt/assets	62/8	-0.3138	6.5369	0.9631	0.9609

Note. The first row reports the lagged maturity coefficient. The remaining rows report lagged intangible additions/assets, CAPEX/assets and debt/assets, respectively, conditional on maturity. Complete-case samples differ.

Table 11. Financial-resource-allocation × AI maturity moderation

Channel	AI × allocation β	Wild p	Interaction Holm-3	Allocation × maturity × annual time β	Triple wild p	Triple Holm
Pooled intangible investment	-136.009	0.5371	1.0000	-70.524	0.2271	0.6812
Nonbank tangible CAPEX	-41.621	0.0781	0.2344	-14.323	0.2500	0.6812
Nonbank financing debt	12.042	0.5000	1.0000	2.648	0.5234	0.6812

Note. Allocation and maturity enter at t−1. Holm-3 adjusts three allocation interactions; the temporal triple interactions have a separate three-comparison family. The time variable is linear annual time, not annual AI evidence.

Direct M/B has a pooled β=−2.6201 (N=98; wild p=0.3921). Among moderated outcomes, the smallest nominal p is 0.0781 for the nonbank CAPEX interaction, rising to Holm-3 = 0.2344. A higher/lower point estimate is not evidence of shareholder value without reliable finite-cluster inference.

Table 12. Annual ROA and CFO/assets downside associations

Model	N / G	β	CR2 SE	df	CR2 p	Holm6 CR2	Wild-C p	Holm6 Wild
ROA decline | all 12 | stage ≥4	108 / 12	-0.02787	0.01518	9.91	0.0964	0.5787	0.0195	0.1172
ROA decline | all 12 | maturity / 5	108 / 12	-0.01170	0.01295	8.94	0.3902	1.0000	0.3848	1.0000
ROA decline | nonbank | stage ≥4	72 / 8	-0.03895	0.02346	6.18	0.1465	0.7324	0.0469	0.2344

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Model	N / G	β	CR2 SE	df	CR2 p	Holm6 CR2	Wild-C p	Holm6 Wild
ROA decline | nonbank | maturity / 5	72 / 8	-0.02883	0.03006	5.24	0.3797	1.0000	0.4375	1.0000
CFO ratio decline | nonbank | stage ≥4	69 / 8	-0.02306	0.02441	6.18	0.3804	1.0000	0.4062	1.0000
CFO ratio decline | nonbank | maturity / 5	69 / 8	-0.03680	0.02873	5.16	0.2549	1.0000	0.2266	0.9062

Note. The six annual financial-stability models use lagged ln assets, lagged cash/assets and firm/fiscal-year-label effects. CR1, CR2 and Rademacher inference is reported with procedure-specific Holm-6 adjustment.

The pooled stage-attainment coefficient on annual ROA decline is −0.02787 (N=108; CR2 p=0.0964; Holm-6 CR2=0.5787), directionally consistent with less measured deterioration but not supported after adjusted tests. The nonbank ROA-downside coefficient is −0.03895 (CR2 p=0.1465; Holm-6=0.7324). The CFO/assets-downside estimates also lack family-adjusted support. Negative-income incidence is only three of 108 firm-years; this is not an adequate rare-event distress panel.

Table 13. Current valuation downside and following-year M/B change

Focal model	N / G	β	CR2 SE	df	CR2 p	WCR-C p	Holm6 CR2	Holm6 WCR-C
M/B decline(t) | all | stage ≥4	95 / 12	+0.4383	0.4963	7.41	0.4049	0.3896	1.0000	1.0000
M/B decline(t) | all | maturity/5	95 / 12	-0.8048	1.1140	6.91	0.4937	0.7646	1.0000	1.0000
ΔM/B(t+1) | all | stage ≥4	86 / 12	+1.3588	1.2791	8.94	0.3159	0.3853	1.0000	1.0000
ΔM/B(t+1) | all | maturity/5	86 / 12	+0.0976	1.3417	6.69	0.9441	0.9385	1.0000	1.0000
ΔM/B(t+1) | all | ROA decline(t), AI controlled	86 / 12	-8.7415	13.5710	1.89	0.5888	0.4849	1.0000	1.0000
ΔM/B(t+1) | nonbank | ROA decline(t), AI controlled	54 / 8	-12.5796	15.6355	2.23	0.4979	0.3516	1.0000	1.0000

Note. The six valuation-extension models use the stated lagged controls and firm/fiscal-year-label effects; subsequent-change models also adjust for current M/B. Holm-6 is applied separately by inferential procedure.

The stage-attainment coefficient on current M/B downside is +0.4383 (N=95; CR2 p=0.4049), positive on the defined downside scale, without significant support. The stage coefficient for next-

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year ΔM/B is +1.3588 (N=86; p=0.3159). Current ROA downside also fails to establish an association with ΔM/B in the next year; all six valuation-family Holm-adjusted CR2 and restricted wild p-values equal 1.0000. The forward sample requires valid listed observations in t and t+1 and excludes 2025 as a current index year; it does not establish real shareholder-wealth preservation.

Table 14. Matched utilization-to-next-year valuation associations (N=57, G=8)

Link	N	β	SE	WCR-S Webb p
Operational attainment → turnover(t)	57	0.1013	0.0339	0.01441
Turnover(t) → M/B(t+1)	57	5.7027	6.4611	0.38999
Operational attainment → M/B(t+1)	57	1.0139	1.1798	0.42958
Operational attainment → average-asset turnover(t)	57	0.1057	0.0349	0.01418
Average-asset turnover(t) → M/B(t+1)	57	6.4857	7.4758	0.31106

Note. The matched nonbank sample is fixed at N=57; the reported links do not identify mediation.

The operational threshold retains a positive association with turnover in the matched valuation sample (β=+0.1013; archived WCR-S Webb p=0.01441), whereas turnover(t) is not reliably associated with M/B(t+1) conditional on the lagged threshold (β=+5.7027; archived WCR-S Webb p=0.38999). The sequence cannot be interpreted as identified mediation. The tested H3 outcomes provide no robust adjusted support; no joint omnibus test of stability and valuation is reported.

Negative coefficients on annual ROA downside indicate smaller fitted declines, not established financial-stabilization effects. Neither exploratory six-test family yields adjusted 5% support. M/B changes measure a valuation multiple, not real, distribution-adjusted shareholder wealth.

9.4. Comparison across AI maturity measures

Table 15 compares annual documentary evidence, historical attainment and prior operational attainment across outcomes. These exposures capture different aspects of maturity and should not be interpreted as repeated independent measurements of the same effect.

Table 15. Cross-domain sensitivity to annual, attained-stage and operational-attainment AI measures

Model	Predictor	N/G	β	CR1 p	Wild p	Holm-12
Relative valuation	Persistent/5	98/12	-2.6201	0.2924	0.3921	1.0000
Relative valuation	Annual evidence /5	98/12	-1.4137	0.3740	0.4888	1.0000
Relative valuation	Stage ≥4 (t−1)	98/12	-0.3366	0.6274	0.5073	1.0000
Intangible investment	Persistent/5	104/12	-0.0185	0.1736	0.1807	1.0000
Intangible investment	Annual evidence /5	104/12	-0.0127	0.1675	0.1914	1.0000
Intangible investment	Stage ≥4 (t−1)	104/12	-0.0098	0.2948	0.3677	1.0000
Asset utilization	Persistent/5	72/8	0.0277	0.5917	0.4609	1.0000
Asset utilization	Annual evidence /5	72/8	0.0156	0.6531	0.5625	1.0000

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Model	Predictor	N/G	β	CR1 p	Wild p	Holm-12
Asset utilization	Stage ≥4 (t−1)	72/8	0.0949	0.0201	0.0078	0.0938
Operating cash flow	Persistent/5	72/8	-0.0900	0.0991	0.0469	0.5156
Operating cash flow	Annual evidence /5	72/8	-0.0475	0.2887	0.3047	1.0000
Operating cash flow	Stage ≥4 (t−1)	72/8	-0.0098	0.7797	0.8047	1.0000

Note. Annual evidence, cumulative attainment and prior stage ≥4 are alternative AI measures. The displayed wild p-values and Holm-12 use exhaustive restricted-null classical WCR-C Rademacher; Table 16 compares procedure-specific archived alternatives.

Associations differ in direction and precision across maturity definitions and financial outcomes. This comparison informs, but does not replace, the hypothesis-level assessment after the robustness and multiplicity checks.

10. Robustness checks and consolidated hypothesis findings

10.1. Robustness and diagnostic evidence

Table 16. Bootstrap procedure and twelve-comparison adjustment

Procedure	Nominal p	Holm-12
WCR-C Rademacher	0.00781	0.09375
WCR-C Webb	0.00378	0.04536
WCR-S Rademacher	0.00781	0.09375
WCR-S Webb	0.00474	0.05688

Note. C denotes classical and S score-adjusted restricted wild bootstrap. WCR-C Rademacher is independently reproduced and is the primary threshold reference; the other rows retain archived procedure-specific results. Holm-12 covers the twelve specified measurements.

Table 17. Company trends and duration model sensitivity

Specification	K	β	CR1 p	WCR-S Webb p
Threshold, with company trends	28	+0.08687	0.0138	0.02124
Duration + threshold + maturity	23	+0.04433	0.0051	0.04946
Duration, with company trends	30	+0.05074	0.1264	0.06715
Duration, log turnover	23	+0.08653	0.0040	0.00364
Duration, log turnover and trends	30	+0.03132	0.7223	0.63684

Note. K is the reported parameter count. Company trends enter only in the indicated rows. Webb p-values in this table are archived WCR-S sensitivity results.

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Table 18. Correlated-effects auxiliary estimates and mean-term tests

Outcome and focal	N / G	β	CR1 p	Means F	Means p
M/B: cumulative maturity	98 / 12	-2.79563	0.2222	2.152	0.13448
M/B: stage 4–5 threshold	98 / 12	-0.62866	0.4931	1.086	0.41984
Intangibles: cumulative maturity	104 / 12	-0.01243	0.3267	0.561	0.72839
Intangibles: stage 4–5 threshold	104 / 12	-0.00504	0.5611	0.387	0.84731
Turnover: cumulative maturity	72 / 8	+0.02774	0.5847	77.694	0.00001
Turnover: stage 4–5 threshold	72 / 8	+0.09493	0.0185	12.476	0.00224
CFO/assets: cumulative maturity	72 / 8	-0.08995	0.0939	13.329	0.00183
CFO/assets: stage 4–5 threshold	72 / 8	-0.00981	0.7755	7.380	0.01030

Note. Mean-term F-tests are correlated-effects specification diagnostics, not causal-identification tests.

The correlated-effects auxiliary suggests that firm-specific unobserved characteristics are related to observed controls, supporting careful use of firm effects rather than a causal reading of coefficients (Table 18). Heteroskedasticity, serial dependence and cross-sectional-dependence screens also caution against treating small-sample inference as definitive.

In the pooled intangible-investment model, the archived residual-dependence screen indicates possible contemporaneous cross-firm correlation ($p = 0.0057$). Adding bank-by-fiscal-year-label terms changes the focal coefficient only modestly (-0.01848 to -0.01831), but does not establish cross-firm error independence. Financial/payment-group-by-year sensitivity likewise absorbs only specified common shocks; bootstrap comparisons appear in Table 16 and Appendix A.

10.2. Consolidated findings for H1–H3

Table 19. Consolidated status of the three grouped hypotheses

Hypothesis	Financial domains	Empirical status	Reporting verdict
H1 — financial decisions	Intangible and tangible investment; nonbank debt; bank asset allocation	No robust 5% focal support	Not supported
H2 — corporate financial performance	Continuous versus attained-stage maturity; nonbank turnover, ROA, CFO and revenue	One positive threshold-turnover finding, sensitive to bootstrap variant, family and denominator; duration attenuates with trends	Qualified exploratory evidence
H3 — financial stability and firm value	Annual downside ROA/CFO; direct, interacted and subsequent M/B; valuation downside	No corrected stability or valuation finding; no matched next-year transmission	Not supported

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Note. Verdicts classify strength of evidence rather than establishing a zero association.

H1—Corporate financial decisions. Estimates for intangible additions, nonbank capital expenditure and financing shares, and bank-specific loan and securities allocation do not provide robust 5% evidence of an association with documented AI maturity. The outcomes represent different investment and balance-sheet decisions rather than a single homogeneous financing response. The tested evidence therefore does not support H1; it does not demonstrate that all economic effects are zero.

H2—Corporate financial performance. Continuous attained maturity is not robustly associated with nonbank turnover, profitability or revenue growth. Prior documented attainment of operational stage 4–5 is positively associated with accounting asset turnover (β=0.09493; N=72, G=8). However, the independently reproduced restricted Rademacher nominal p-value of 0.0078125 becomes Holm-12=0.09375. The association is also sensitive to denominator definitions, sample composition and fiscal periods, with only six nonbanks changing attainment status. H2 is therefore not confirmed at the 5% family level; the turnover finding remains exploratory.

H3—Financial stability and firm value. The specified indicators of adverse annual accounting changes, direct and allocation-conditional market-to-book, and subsequent relative valuation do not retain robust family-adjusted 5% support. The matched turnover-to-next-year valuation models likewise do not establish a reliable link or a causal transmission mechanism. The tested evidence does not support H3; the non-rejection of individual null hypotheses is not evidence of an economically zero effect.

The following discussion addresses the economic interpretation of these findings in relation to earlier research, rather than repeating the regression tables.

11. Discussion in relation to previous studies

The empirical evidence reveals a distinction between documented advances in AI-related organizational capability and observable financial outcomes. Rather than treating the absence of a statistically robust association as proof that AI has no value, the analysis asks which financial measures and maturity representations yield comparable evidence, and why seemingly divergent findings in the literature may concern different economic objects.

11.1. AI maturity and corporate financial decisions

The absence of robust associations between documentary AI maturity and intangible additions, nonbank capital expenditure or financing shares contrasts with the positive investment-efficiency results reported by (Chen, Kim, & Peng, 2026), (Hsu, Lee, Gong, & Chuang, 2026), (Lou, Li, & Tong, 2025); (Li, Liao, & Tang, 2026). The distinction is substantive rather than simply statistical: these studies evaluate the quality of project selection, departures from expected investment or policy-related allocation efficiency, whereas the present outcomes record investment intensity and balance-sheet composition. A firm could reallocate capital toward better projects without raising total CAPEX or identifiable intangible additions. Accordingly, our estimates neither replicate nor overturn claims concerning investment efficiency; they address whether documentary maturity accompanies a measurable change in the volume or composition of financial commitments.

The funding evidence offers a second comparison. (Damle & Sinha, 2025) associate U.S. AI-related investment with greater cash reserves and relatively greater use of internal funds and equity,

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whereas (Yu & Cong, 2026) document tighter financing constraints, particularly for private companies. Precautionary liquidity, financing frictions and observed borrowing can move differently, so they are not opposing estimates of an identical parameter. The lack of a robust debt/assets association in our nonbank firms cannot adjudicate between these mechanisms. Meanwhile, bank lending and investment securities reflect uses of funds, not the same financing choice measured by corporate debt in nonbanks. This sectoral distinction narrows the claims we can make, but prevents a misleading pooled interpretation of unlike balance-sheet margins.

11.2. AI maturity and corporate financial performance

The largely inconclusive associations for profitability, revenue growth and continuous maturity differ from evidence of AI-linked sales expansion and innovation in (Babina, Fedyk, He, & Hodson, 2024) and productivity gains in (Czarnitzki, Fernández, & Rammer, 2023), (Wu & Zhu, 2025); (Park, Kang, Yi, & Kim, 2026). These studies typically observe technology investment, adoption intensity, skilled labor or total factor productivity, whereas this study records stages of documentary maturity and accounting outcomes. Increased output per worker or total factor productivity need not produce a contemporaneous improvement in ROA or revenue divided by assets, particularly if new technologies require complementary spending or organizational adjustment. The attenuation of initially favorable profitability differences after firm controls in (Guettoufi, 2026) is closer to our nonrobust profitability pattern, without implying a direct replication across distinct markets and samples.

An economically interesting but qualified pattern emerges when previously attained operational implementation is distinguished from continuous documentary maturity. Prior stage attainment is positively associated with nonbank accounting asset turnover, which is compatible with the possibility that operational milestones differ from mere preparation in their financial manifestation. Yet the coefficient does not retain 5% family-adjusted support, and changes in the asset denominator, fiscal-period restrictions and firm composition matter. Only six nonbanks supply within-firm changes in the lagged attainment indicator. The evidence therefore motivates examination of stage-dependent financial outcomes, but it does not establish a discrete productivity threshold or show that operational implementation itself generated additional revenue.

The contrast also qualifies how the literature's complementarity argument should be applied. Organizational capability and implementation purpose may mediate eventual productivity benefits, as emphasized by (McElheran, et al., 2024); (Park, Kang, Yi, & Kim, 2026), but the current specifications do not observe those mechanisms directly. We interpret the threshold result as a hypothesis-generating accounting association rather than a verified transition from technological maturity to firm-wide efficiency.

11.3. AI maturity, financial stability and firm value

No family-adjusted evidence links documentary maturity consistently to the selected financial-stability proxies. (El Moujahid, Murtinu, & Sekerci, 2026) consider stock performance and volatility around an identified crisis, while (Chen, Liu, Chen, Wang, & Zhang, 2026) examine resistance, recovery and funding continuity. Those outcomes characterize responses to shocks or broader resilience; our annual adverse changes in ROA and operating cash-flow ratios measure a narrower aspect of accounting performance. The apparent difference in significance cannot therefore be read as a contradiction of identical stability effects. (Le & Wu, 2026) further show that initially favorable

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banking return–risk patterns may weaken over time, underscoring why an observed operating gain should not be equated with sustained stability.

The valuation results similarly warrant comparison by outcome and exposure. (Babina, Fedyk, He, & Hodson, 2024); (Chen, Kim, & Peng, 2026) associate distinct AI measures with higher valuations; (Eisfeldt, Schubert, Zhang, & Taska, 2026) examine repricing around a technology-related event, rather than the annual market-to-book multiple used here. Our unsupported contemporaneous and forward M/B associations do not disprove those findings, but fail to show that the documented stages in this cohort are accompanied by a reliably higher relative valuation. Evidence from (Bai, Zhao, & Liu, 2026); (Li Z. , 2026), connecting optimistic AI narratives or disclosure gaps to market risks, also illustrates why investors' capitalization of expected benefits need not coincide with realized or stable financial gains.

Crucially, a positive operating-stage association with asset turnover and an unsupported turnover-to-following-year valuation link are not evidence of a tested causal mediation chain. Different reporting horizons, financial structures and investor expectations may influence the correspondence between operating outcomes and value, but this dataset cannot identify which explanation dominates.

11.4. Financial implications and future research

The findings highlight the importance of distinguishing between advances in documented artificial intelligence (AI) maturity and the realization of tangible financial benefits. Attaining advanced stages of technological maturity does not necessarily translate into simultaneous improvements in corporate investment and financing decisions, financial performance, financial stability, or firm value. The findings also underscore the need to distinguish investment intensity from resource allocation efficiency, asset utilization from productivity, and partial indicators of financial stability from comprehensive financial resilience, thereby enabling a more accurate assessment of the financial relationships associated with technological advancement.

From a practical perspective, the findings highlight the importance of distinguishing between firms' stated AI ambitions, verifiable stages of implementation, and financial benefits reflected in reported outcomes. Corporate disclosures should therefore extend beyond general statements of technological intentions or maturity to provide more specific information on AI-related expenditures, the scope of actual implementation, and associated operational and financial outcomes. Greater transparency in these areas could help investors and managers assess resource allocation decisions and financial prospects more accurately, without presuming that documented AI maturity alone generates economic value or warrants a valuation premium.

Accordingly, the study provides a foundation for future research employing more direct measures of AI investment and actual utilization, larger samples, longer observation periods, and research designs better suited to identifying the mechanisms through which potential operational benefits may translate into financial stability and value creation.

Appendices

The following tables report additional sensitivity analyses of the association between prior attainment of an operational AI implementation stage and asset turnover among nonbank firms. The sample exclusions are exploratory checks rather than separate hypotheses.

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Table A1. Sensitivity of the operational-attainment–asset-turnover association to sample composition

Specification	N / G	B	CR1 SE	Rademacher p	Exposed observations / switching firms
Baseline sample	**72 / 8**	**+0.09493**	**0.03170**	**0.0078125**	**25 / 6**
Excluding EFIG and FWRY	**54 / 6**	**+0.10890**	**0.04204**	**0.0312500**	**22 / 5**
Excluding HRHO	**63 / 7**	**+0.10669**	**0.03771**	**0.0312500**	**19 / 5**
Excluding EFIG, FWRY, and HRHO	**45 / 5**	**+0.13316**	**0.04771**	**0.1250000**	**16 / 4**

Note: All specifications are re-estimated using the same firm and year fixed effects and controls. Reported p-values are nominal and are based on exhaustive enumeration of firm-level sign patterns in the restricted Rademacher test. The coefficient remains positive, but weaker inference in some subsamples indicates sensitivity to sample composition rather than independent confirmation.

Table A2. Comparison of inference procedures for the operational-attainment–asset-turnover association

Inference procedure	Nominal p-value	Holm-12 adjusted p-value
Restricted WCR-C Rademacher (exact enumeration)	**0.0078125**	**0.0937500**
Score-adjusted WCR-S Webb (archived results)	**0.0047400**	**0.0568800**
Conventional WCR-C Webb (archived results)[1]	**0.0037800**	**0.0453600[1]**

Note: The Rademacher result was independently reproduced. The Holm-12 adjustment for score-adjusted WCR-S Webb was independently recalculated from the original vector of p-values, but the underlying bootstrap algorithm was not rerun. [1] The WCR-C Webb Holm-12 value is reported as archived; its full family-level p-value vector was unavailable for independent verification. Unlike the other two adjusted results, it is below 5%; accordingly, the three procedures do not provide a consistent confirmatory conclusion at this level.

References :

Arellano, M. (1987). Computing robust standard errors for within-groups estimators. *Oxford Bulletin of Economics and Statistics*, 49(4), 431–434. https://doi.org/10.1111/j.1468-0084.1987.mp49004006.x.

Babina, T. (2026). Understanding firms' AI efforts and their economic impact. *The Review of Corporate Finance Studies*, 15(4), 967–1013. https://doi.org/10.1093/rcfs/cfag027.

Print ISSN 2771-1161
Online ISSN 2771-1153

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151, Article 103745. https://doi.org/10.1016/j.jfineco.2023.103745.

Bai, X., Zhao, W., & Liu, M. (2026). Artificial intelligence and stock price crash risk: Evidence from China: A pre-registered study. *Pacific-Basin Finance Journal*, 96, Article 103039. https://doi.org/10.1016/j.pacfin.2025.103039.

Basnet, A., Elias, M., Salganik-Shoshan, G., Walker, T., & Zhao, Y. (2025). Analyzing the market's reaction to AI narratives in corporate filings. *International Review of Financial Analysis*, 105, Article 104378. https://doi.org/10.1016/j.irfa.2025.104378.

Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, 140(2), 889–942. https://doi.org/10.1093/qje/qjae044.

Cameron, A. C., & Miller, D. L. (2025). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, 50(2), 317–372. https://doi.org/10.3368/jhr.50.2.317.

Chen, S., Kim, J., & Peng, S. (2026). The real effects of AI: Evidence from corporate investment efficiency. *Journal of Empirical Finance*, 88, Article 101730. https://doi.org/10.1016/j.jempfin.2026.101730.

Chen, X., Liu, W., Chen, G., Wang, X., & Zhang, Y. (2026). Can artificial intelligence enhance corporate resilience? Empirical evidence from China's A-share listed firms. *Pacific-Basin Finance Journal*, 97, Article 103112. https://doi.org/10.1016/j.pacfin.2026.103112.

Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization*, 211, 188–205. https://doi.org/10.1016/j.jebo.2023.05.008.

Damle, H., & Sinha, R. K. (2025). Does corporate investment in artificial intelligence affect cash holdings? *The British Accounting Review*, Article 101731. Advance online publication. https://doi.org/10.1016/j.bar.2025.101731.

Deng, X., & Qin, C. (2026). Artificial intelligence and corporate financialization. *International Review of Financial Analysis*, 110, Article 104906. https://doi.org/10.1016/j.irfa.2025.104906.

Dong, Q., Wang, K., & Lian, L. (2026). The impact of artificial intelligence on corporate debt default risk: From the perspective of resource orchestration and risk response. *Research in International Business and Finance*, 91, Article 103575.https://doi.org/10.1016/j.ribaf.2026.103575.

Eisfeldt, A. L., Schubert, G., Zhang, M. B., & Taska, B. (2026). Generative AI and firm values. *The Journal of Finance*, Advance online publication. https://doi.org/10.1111/jofi.70089.

El Moujahid, O., Murtinu, S., & Sekerci, N. (2026). Artificial intelligence and firm resilience. *Journal of Financial Stability*, 84, Article 101542. https://doi.org/10.1016/j.jfs.2026.101542.

CC BY

Fan, C., Liao, X., & Yang, X. (2025). Artificial intelligence and enterprise total factor productivity: A human capital requirement perspective. *International Review of Economics & Finance*, 104, Article 104661. https://doi.org/10.1016/j.iref.2025.104661.

Financial Regulatory Authority. (2026). Financial technology. https://fra.gov.eg/en/المالية-التكنولوجيا/ .

Fu, X., Zhang, Q., Sun, M., Liu, J. Y., & Lu, Y. (2026). The impact of artificial intelligence development on enterprise labor investment efficiency. *International Review of Economics & Finance*, 107, Article 105157. https://doi.org/10.1016/j.iref.2026.105157.

Guettoufi, Y. (2026). Assessing the impact of artificial intelligence adoption on corporate financial performance: Evidence from emerging markets. *International Review of Economics & Finance*, 108, Article 105272. https://doi.org/10.1016/j.iref.2026.105272.

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 6(2), 65–70. https://www.jstor.org/stable/4615733.

Hsu, F., Lee, C., Gong, F., & Chuang, C. (2026). Does corporate AI adoption improve investment efficiency? Evidence from textual analysis of 10-K filings. *Finance Research Letters*, 107, Article 110366. https://doi.org/10.1016/j.frl.2026.110366.

Jian, W., Lu, H., Yang, Z., & Zhong, Z. (2026). The sustainability payoff of AI: Revisiting TFP in corporate and societal performance. *International Review of Financial Analysis*, 110, Article 104891. https://doi.org/10.1016/j.irfa.2025.104891.

Khalil, M. A., & Abdelraouf, M. (2026). The era of AI: Development of artificial intelligence (AI) and its effect on advancing banks profitability: The role of financial stability as moderating variable in Egyptian banks. *Journal of the Knowledge Economy*, 17(4), 11411–11446. https://doi.org/10.1007/s13132-026-03268-0 .

Koenker, R. (1981). A note on studentizing a test for heteroscedasticity. *Journal of Econometrics*, 17(1), 107–112. https://doi.org/10.1016/0304-4076(81)90062-2.

Le, M. D., & Wu, M. W. (2026). Which cases do commercial banks fall into after adopting artificial intelligence? Evidence from the Asia-Pacific. *International Journal of Finance & Economics*, Advance online publication. https://doi.org/10.1002/ijfe.70284.

Li, W., Liao, W., & Tang, X. (2026). Artificial intelligence and corporate investment efficiency: Quasi-experimental evidence from China. *Research in International Business and Finance*, 88, Article 103433. https://doi.org/10.1016/j.ribaf.2026.103433.

Li, Y., Zhong, H., & Tong, Q. (2024). Artificial intelligence, dynamic capabilities, and corporate financial asset allocation. *International Review of Financial Analysis*, 96, Article 103773. https://doi.org/10.1016/j.irfa.2024.103773.

Li, Z. (2026). Does artificial intelligence enhance bank profitability? Evidence from China. *Finance Research Letters*, 90, Article 109366. https://doi.org/10.1016/j.frl.2025.109366.

Print ISSN 2771-1161
Online ISSN 2771-1153

Lin, N., Li, A., Geng, Y., Yao, J., & Liu, C. (2026). The role of artificial intelligence in enhancing firm investment efficiency. *International Review of Financial Analysis*, 109, Article 104830. https://doi.org/10.1016/j.irfa.2025.104830.

Liu, S., Gao, L., & Chen, M. (2025). Artificial intelligence adoption and corporate financial risk. *Finance Research Letters*, 85, Article 107938. https://doi.org/10.1016/j.frl.2025.107938.

Liu, Y., & Hu, R. (2025). Artificial intelligence, supply chain finance, and corporate investment efficiency. *Finance Research Letters*, 85, Article 107851. https://doi.org/10.1016/j.frl.2025.107851.

Lou, Z., Li, C., & Tong, C. (2025). Artificial intelligence and corporate investment efficiency. *International Review of Economics & Finance*, 104, Article 104713. https://doi.org/10.1016/j.iref.2025.104713.

MacKinnon, J. G., & Webb, M. D. (2018). The wild bootstrap for few (treated) clusters. *The Econometrics Journal*, 21(2), 114–135. https://doi.org/10.1111/ectj.12107.

McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., et al. (2024). AI adoption in America: Who, what, and where. *Journal of Economics & Management Strategy*, 33(2), 375–415. https://doi.org/10.1111/jems.12576.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, 46(1), 69–85. https://www.jstor.org/stable/1913646.

National Council for Artificial Intelligence. (2025). Egypt national artificial intelligence strategy. *Second edition (2025–2030)*, https://ai.gov.eg/SynchedFiles/en/Resources/AIstrategy%20English%2016-1-2025-1.pdf.

Park, G., Kang, S., Yi, S., & Kim, J. (2026). Diverse impacts of AI investments on productivity gains: Effects of industry and innovation characteristics. *Technological Forecasting and Social Change*, 224, Article 124471. . https://doi.org/10.1016/j.techfore.2025.124471.

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. *Cambridge Working Papers in Economics*, 0435. https://doi.org/10.17863/CAM.5113.

Pustejovsky, J. E., & Tipton, E. (2018). Small-sample methods for cluster-robust variance estimation and hypothesis testing in fixed effects models. *Journal of Business & Economic Statistics*, 36(4), 672–683. https://doi.org/10.1080/07350015.2016.1247004.

Shi, Y., Wu, T., Qin, C., & Liu, B. (2025). The value-creating potential of AI: A multi-dimensional analysis of effects and mechanisms. *International Review of Financial Analysis*, 108, Article 104694. https://doi.org/10.1016/j.irfa.2025.104694.

Sun, Q., & Huang, M. (2026). Firm-level evidence on AI-driven output expansion and productivity in China. *Socio-Economic Planning Sciences*, 103, Article 102389. https://doi.org/10.1016/j.seps.2025.102389.

CC BY

Wu, X., & Zhu, Y. (2025). How artificial intelligence applications affect the total factor productivity of the service industry: Firm-level evidence from China. *Journal of Asian Economics*, 97, Article 101893. https://doi.org/10.1016/j.asieco.2025.101893.

Xing, X., Zhang, Z., & He, W. (2026). AI technology, AI narrative, and firm value. *Technovation*, 149, Article 103349. https://doi.org/10.1016/j.technovation.2025.103349.

Yang, L. (2026). AI washing: How does it influence firm value? *Finance Research Letters*, 104, Article 110210. https://doi.org/10.1016/j.frl.2026.110210.

Yu, H., & Cong, S. (2026). Too advanced to afford? Artificial intelligence investment and financial constraints. *Finance Research Letters*, 106, Article 110334. https://doi.org/10.1016/j.frl.2026.110334.

Zhang, J., Cui, C., Zheng, C., & Taylor, G. (2025). Artificial intelligence innovation and stock price crash risk. *Journal of Financial Research*, 48(2), 503–543. https://doi.org/10.1111/jfir.12424.

Zhang, X., Wang, Y., & Yin, X. (2026). Artificial intelligence technology, intellectual property protection, and financing constraints of technology firms. *Finance Research Letters*, 109, Article 110576. https://doi.org/10.1016/j.frl.2026.110576.

Print ISSN 2771-1161
Online ISSN 2771-1153