The Impact of Artificial Intelligence on the Cost of Capital

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Abstract: This paper asks whether adopting artificial intelligence (AI) lowers firms' required returns—or instead raises perceived uncertainty—and why effects differ across firms and markets. Building on finance theories of information risk and control, we develop a framework in which AI affects the cost of capital through three channels: risk estimation (forecastability of cash flows), risk transformation (tail exposure and correlated failure risk), and governance credibility (legibility, auditability, and accountability of AI-driven decisions). The central prediction is conditionality: AI can improve operating performance yet generate little average decline in the cost of capital when opacity or control concerns offset cash-flow gains. Financing benefits arise when disclosure and governance make AI use verifiable and constrain downside risk, with particularly strong implications for debt markets and mature firms. The framework motivates a governance-interacted staggered-adoption difference-in-differences design and clarifies why prior evidence on technology adoption and financing outcomes is mixed. It also yields sharp implications for FinTech valuation, where AI is often the core production technology and capital pricing hinges on credible oversight.

Keywords: Information asymmetry, Risk, FinTech valuation, Discount-rate, Enterprise value, FinTech governance, AI regulation, Sustainable digital finance.

1. INTRODUCTION

AI adoption is widely associated with productivity gains and innovation, but its implications for capital pricing remain unsettled. The cost of capital reflects not only expected cash flows, but also how investors and creditors assess uncertainty, interpret information, and trust managerial control. AI is distinctive because it can simultaneously (i) improve decisions that shape cash flows and (ii) increase opacity and model dependence in the processes generating those cash flows. As a result, the core finance question is not if AI improves operating performance, but *whether AI reduces priced uncertainty in capital markets—or instead introduces new forms of uncertainty for which investors require compensation*.

This paper argues that AI adoption affects required returns indirectly—by changing the information environment and the credibility of control—so its effect on the cost of capital is conditional rather than mechanical. We develop a finance-oriented framework with three channels. Risk estimation assesses whether adoption facilitates the forecasting of future cash flows (*e.g.*, by providing clearer signals and lower dispersion). Risk transformation captures whether AI alters the distribution of outcomes (*e.g.*, tail risk, model/data shocks, or correlated vendor or architectural dependencies). Governance credibility concerns whether outsiders perceive AI-driven decisions as constrained, auditable, and accountable, particularly when decision authority is delegated to algorithms. Together, these channels imply that AI can raise expected cash flows while leaving required returns unchanged—or even higher—when AI use is hard to verify or govern.

Importantly, we do not test whether AI is 'good or bad' for firms, but whether and when capital markets price AI adoption as a reduction in risk.

The paper's added value lies in reframing AI adoption as a capital-pricing technology rather than an operational technology. This perspective yields testable predictions about (i) why average effects on the cost of capital can be weak even when performance improves, (ii) why conditional effects should be stronger in debt markets, where monitoring and downside risk dominate, and (iii) why effects should be particularly sharp in FinTechs, where AI often replaces human judgment and becomes central to value creation and regulatory scrutiny (Moro-Visconti, 2024). Empirically, the framework motivates a staggered-adoption difference-in-differences design with governance interactions and event-time diagnostics to separate cash-flow improvements from discount-rate responses. Our core contribution is to show that AI adoption is priced primarily through belief formation—via estimation risk, tail-risk perceptions, and governance credibility—so operating gains do not mechanically translate into lower required returns.

2. LITERATURE REVIEW

Prior research suggests that AI and digital technologies can raise performance and valuations, but it does not follow that they systematically lower required returns. Babina, Fedyk, He, and Hodson (2024) document that AI investment is associated with faster growth and higher valuations, consistent with a cash-flow channel. Evidence using large language model–based adoption measures likewise points to

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operational and financial benefits from digital technology adoption (Li, Li, Zhao, & Zhao, 2025). These findings support the view that AI can improve expected fundamentals. Still, they leave open the question of whether capital providers view the resulting cash flows as *more predictable and controllable*—the key determinant of discount rates.

A related literature embeds AI directly into valuation models. Chauhan (2025) and Nag (2025) demonstrate how machine learning forecasts can be integrated into DCF and LBO analyses to improve cash flow estimation, while Lu and Zhao (2025) develop probabilistic, ML-enhanced DCF models that sharpen scenario analysis. This work demonstrates that AI can materially affect valuation inputs. Still, it largely abstracts from how capital markets price the resulting uncertainty and governance concerns—an omission our framework addresses by focusing on required returns rather than valuation mechanics.

A second strand emphasizes the role of complexity in forecasting and pricing. Kelly, Malamud, and Zhou (2024) show that complexity can improve return prediction, underscoring that the information-processing environment matters for asset prices. Loughran and McDonald (2024) further argue that "complexity" is multi-dimensional and difficult to measure with simple proxies. These insights motivate our focus on risk estimation: AI can either reduce uncertainty by improving signals or increase it by adding model and organizational complexity that outsiders struggle to interpret.

A third strand links disclosure and information risk to required returns. Rjiba, Saadi, Boubaker, and Ding (2021) show that less readable annual reports are associated with a higher cost of equity, consistent with higher information-processing costs and greater estimation risk. In the digital transformation literature, Ren, Liu, and Hao (2024) find that digital transformation is associated with a lower cost of equity and highlight the role of disclosure quality and liquidity in transmitting the effect. Yet, technology-related disclosure can also be interpreted as a risk signal. Hussien, Ibrahim, and Albitar (2025) document a positive relationship between digital-technology disclosure and the cost of capital, consistent with markets perceiving heightened uncertainty (with sustainability performance mediating the effect). Together, these studies support our core claim: financing outcomes depend on whether adoption and disclosure reduce or increase priced uncertainty.

Finally, recent work emphasizes credibility and measurement. Zhu (2025) models mandatory AI-risk disclosure as a signalling device, highlighting how credible disclosure can separate high- from low-quality adopters when true AI capabilities and risks are not directly observable. In parallel, Bussmann, Giudici, Tanda, and Yu (2025) show—using explainable machine learning to predict ex ante cost of capital—that governance and institutional features are central predictors of required returns, consistent with the view that "governance" is not a peripheral control but part of the pricing mechanism.

Our contribution is to unify these strands into a single finance mechanism that explains why AI can boost performance without lowering average required returns, and why governance and disclosure should sort outcomes across equity and debt markets. The framework has particularly sharp implications for FinTech valuation, where AI is often the core production technology and capital pricing hinges on auditability, explainability, and credible human oversight (Moro-Visconti, 2024).

3. AI, UNCERTAINTY, AND CAPITAL PRICING: CHANNELS AND HYPOTHESES

This paper asks whether adopting AI lowers firms' required returns—or instead raises perceived uncertainty—and why the effects differ across firms and markets. In standard asset-pricing models, expected returns reflect exposure to systematic risk. In practice, required returns also embed estimation risk, information frictions, and confidence in managerial control. AI is unusual because it can shift all three at once, often in opposite directions.

AI can improve decision-making by extracting signals from large, high-dimensional datasets. Better forecasting, more disciplined execution, and less decision noise can make cash flows more predictable. If these improvements are visible and credible to outsiders, required returns should fall.

At the same time, AI can create new uncertainty. Many systems are complex, partly opaque, and sensitive to changes in data and retraining. Investors typically observe outcomes rather than the underlying decision process. When they cannot evaluate how models work, adapt, or fail, estimation risk can rise even if operating performance improves.

AI can also transform the shape of risk. Average gains may coexist with heavier tails, nonlinear failures, and correlated breakdowns across firms using similar models, data, vendors, or architectures. When these downside risks are difficult to stress-test or are perceived as non-diversifiable, capital providers may demand higher premia, particularly in debt markets where downside protection and monitoring are central.

These considerations imply that AI adoption is not priced as a mechanical improvement in firm quality. Its effect on required returns depends on how AI changes (i) the information environment faced by capital providers, (ii) perceived downside tail exposure, and (iii) confidence in governance and control. Accordingly, our framework treats AI as a capital-pricing technology: it can raise expected cash flows while simultaneously altering outsiders' beliefs about forecastability, tail risk, and accountability. Because these forces can offset one another, the average effect of AI adoption on the cost of capital is theoretically ambiguous. The key prediction is conditionality: financing benefits arise only when AI use is legible to capital providers and credibly constrained by governance.

We formalize these mechanisms in five hypotheses that map directly into the empirical tests in Section 4 and are evaluated using operating outcomes, required-return measures, and debt-market pricing.

3.1. Information Channel: Estimation Risk and Disclosure

AI can enhance internal information processing (*e.g.*, forecasting, pricing, credit assessment, and planning). If the resulting performance improvements are visible and credibly communicated, investors can forecast cash flows with higher precision. This reduces information asymmetry and lowers estimation risk, thereby lowering required returns.

But AI can also make the cash-flow-generating process harder to interpret. If disclosure is vague, if models are black-box or proprietary, or if outsiders cannot understand failure modes, performance may look fragile and difficult to extrapolate. In that case, estimation risk rises, and required returns need not fall.

H1 (Operating performance/cash-flow channel).

AI adoption is associated with higher expected operating cash flows (or operating performance) relative to otherwise similar non-adopting firms.

H2 (Information and disclosure: estimation-risk conditionality).

AI adoption is consistently associated with a *lower* cost of capital only when AI use improves the external information environment—*i.e.*, when AI-related improvements are observable, interpretable, and credibly disclosed. When AI use is opaque, the effect is weaker, absent, or reversed.

How it is answered later: Section 4 tests H1 using operating outcomes (*e.g.*, OCF/EBITDA/margins) and tests H2 by interacting AI adoption with disclosure/readability/specificity proxies and by examining information-environment outcomes (*e.g.*, analyst disagreement/forecast dispersion).

3.2. Risk Channel: Tail Exposure and Correlated Failure

AI can reduce routine operational mistakes and improve consistency, potentially lowering idiosyncratic noise. At the same time, it can introduce difficult-to-price exposures, such as model risk, data shocks, distribution shifts, feedback loops, and correlated failures across shared vendors, architectures, or datasets. For capital providers, the central question is whether AI makes outcomes more forecastable or more fragile in the tail.

H3 (Risk transformation: tail-risk pricing).

AI adoption is associated with a higher (or non-decreasing) cost of capital when it increases perceived downside risk—especially when AI-related risks are nonlinear, hard to stress-test/hedge, or correlated across firms.

Section 4 links AI adoption to downside-risk proxies (*e.g.*, crash risk/tail measures, where available) and tests whether required returns/spreads worsen as risk-transformation indicators increase.

3.3. Governance Channel: Credibility of Oversight and Control

Required returns also reflect whether outsiders believe the firm can control the technology shaping outcomes. AI can blur accountability through automated decision-making, continuous learning, and vendor/data dependence. When oversight is weak, or override authority is unclear, investors—especially creditors—may fear hidden risk-taking and loss of control.

Credible AI governance can mitigate these concerns. Clear accountability, documented model objectives, validation and audit trails, traceability, vendor/data controls, and explicit human-in-the-loop authority make AI use more verifiable and reduce monitoring costs.

H4 (Governance credibility: control-conditional pricing).

The effect of AI adoption on the cost of capital is more negative (or less positive) when AI governance is stronger—*i.e.*, when oversight makes AI use auditable, controllable, and credible to outsiders.

How it is answered later: Section 4 tests H4 by interacting AI adoption with pre-adoption governance and auditability proxies (board/controls/audit quality/AI governance disclosures) and examining whether required-return outcomes improve more for well-governed adopters.

3.4. Debt Versus Equity Implications

Debt pricing is particularly sensitive to downside outcomes, monitoring frictions, and control rights. Therefore, the conditional effects driven by tail risk and governance credibility should be stronger in debt markets than in equity markets.

H5 (Debt versus equity: stronger conditionality in credit markets).

The governance- and downside-risk–conditioned effects of AI adoption on financing costs are stronger for debt (credit spreads, loan rates, ratings) than for equity discount-rate measures.

Supporting H5, Section 4, and the empirical strategy compares debt outcomes (spreads/ratings/loan pricing) with equity required-return proxies and tests whether governance interactions are larger in magnitude in credit markets.

4. MODEL AND TESTABLE HYPOTHESES

This section converts the channel framework into an empirical design that directly answers the research question. The design separates:

- Cash-flow effects (whether AI improves operating performance), and
- Discount-rate effects (whether markets require lower returns once AI is adopted, and under what conditions).

Because AI can raise expected cash flows while simultaneously increasing perceived uncertainty or weakening perceived control, the unconditional average effect on the cost of capital is not predicted to be uniformly negative. The empirical tests, therefore, focus on conditionality via disclosure, risk, and governance.

4.1. Empirical Hypotheses The Hypotheses Tested in the Empirical Section are Exactly the Five Hypotheses Developed Above

H1 (Operating performance).

AI adoption increases expected operating cash flows/operating performance.

H2 (Disclosure and information environment).

AI adoption lowers the cost of capital only when disclosure quality and interpretability are high; opaque AI use weakens or reverses the effect.

H3 (Downside risk).

AI adoption does not lower (and can raise) the cost of capital when perceived AI-related downside/tail risk increases.

H4 (Governance credibility).

AI adoption lowers the cost of capital more when AI governance is strong and auditable.

H5 (Debt vs. equity).

The conditional effects in H2–H4 are stronger in debt markets than in equity markets.

These five hypotheses ensure internal consistency: Section 3 states the mechanisms; Section 4 tests the same five predictions; and later results sections can explicitly address each hypothesis (performance, discount rates, credit pricing, and heterogeneity by disclosure/governance/risk).

Table **1** presents a counterfactual difference between the absence and adoption of AI.

Interpretation: Table **1** makes clear why “AI improves operations” (H1); it does *not* mechanically imply that “AI lowers the cost of capital” (H2/H3). The sign depends on whether AI is predicted to reduce *priced uncertainty* (risk estimation + tail perceptions) and whether governance makes AI outcomes *credible* to investors.

4.2. Baseline Specification

To test the model’s predictions, estimate panel regressions of the form:

$$Y\_\{i,t\} = \alpha + \beta\ AI\_\{i,t\} + \gamma\_i + \delta\_t + X\_\{i,t\}'\ \theta + \varepsilon\_\{i,t\} \qquad (1)$$

- Y_{i,t} denotes a financing outcome, including the implied cost of equity, bond yield spreads, credit ratings, or analyst forecast dispersion.
- AI_{i,t} is an indicator (or intensity measure) of artificial intelligence adoption by firm i in period t.
- γ_i and δ_t represent firm fixed effects and time fixed effects, respectively.

X_{i,t} is a vector of controls, including firm size, leverage, profitability, return volatility, investment, and liquidity.

Table 1: Without vs. With AI Comparison

Channel (from Section 3)	Without AI adoption (baseline)	With AI adoption (expected change)	Observable empirical proxy	Predicted sign for outcomes	Hypotheses
Cash-flow channel (productivity/decision quality)	More forecasting noise; slower adaptation; greater operational inefficiency	Higher forecast accuracy; improved allocation; smoother operations → ↑ expected OCF/FCFF	OCF, EBITDA, margins, forecast errors, and inventory turns	Performance: ↑	H1
Information asymmetry & risk estimation (Prop. 1)	Investors rely on traditional disclosures and historical volatility	Two regimes: (a) transparency/verification improves → ↓ risk estimation or (b) opacity increases → ↑ risk estimation	Analyst forecast dispersion, bid–ask spreads, earnings response coefficients, disclosure indices, and textual clarity	Cost of equity: ↓ under (a), ambiguous/↑ under (b)	H2
Risk transformation/tail exposure (Prop. 2)	Risk is primarily operational and historically measurable	Idiosyncratic risk may fall, but model/data risk and fat tails may rise; correlated failures are possible	Crash risk measures, downside beta, tail-risk metrics, volatility of fundamentals, "AI incident" exposures	Required returns: ↓ if perceived diversifiable; ↑ if perceived systematic/opaque	H2, H3
Governance credibility & control (Prop. 3)	Governance is assessed through standard internal controls and oversight	AI introduces autonomy/vendor dependence; strong controls can restore credibility (validation, audit trails, human oversight)	AI governance disclosures, internal-control strength, audit quality, risk committee indicators, and model validation policies	Cost of capital: ↓ When governance is credible, the debt market reacts strongly	H2, H3
Valuation nonlinearity (discount-rate dominance in mature firms)	Value is primarily tied to stable cash flows discounted at WACC	Small changes in required returns can dominate moderate EBITDA gains when duration is long	Decomposition of valuation changes; implied cost of equity; WACC	Firm value: more sensitive to Δk than ΔEBITDA in mature firms	H4

The coefficient (b) captures the average association between AI adoption and capital-market outcomes. Because AI can simultaneously raise expected cash flows and raise perceived uncertainty, (b) is not predicted to be uniformly negative for required-return outcomes.

4.3. Difference-in-Differences Interpretation

The baseline specification admits a difference-in-differences interpretation by comparing adopters to non-adopters before and after adoption. Identification relies on the parallel trends assumption: absent AI adoption, financing outcomes for adopters would have evolved similarly to those for non-adopters.

We assess this assumption using:

- pre-trend diagnostics, and
- event-study specifications tracing financing outcomes in event time around adoption.

4.4. Governance and Conditional Effects (Core Test)

To test the conditional predictions, estimate:

$$Y_{i,t} = \alpha + \beta 1\ AI_{i,t} + \beta 2\ (AI_{i,t} \times Governance_{i,t}) + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

Variable Definitions

- Y_{i,t} denotes a financing outcome for firm i in period t.
- AI_{i,t} measures the adoption or intensity of artificial intelligence use.
- Gov_i captures pre-adoption AI-related governance quality, including disclosure transparency, auditability, internal controls, and explicit AI governance policies.
- γ_i and δ_t represent firm fixed effects and time fixed effects, respectively.
- ε_{i,t} is the error term.

Key Predictions

- The coefficient β_1 is expected to be small, ambiguous, or potentially adverse to required-return outcomes, reflecting the possibility that AI adoption increases opacity, model risk, or tail risk.
- The interaction coefficient $\beta_2$is predicted to be negative for required-return outcomes (such as the implied cost of equity or bond yield spreads), indicating that strong governance mitigates

AI-related uncertainty by transforming AI from a perceived "black-box risk" into a credible and monitorable technology.

This specification is the empirical counterpart to Propositions 1–3.

4.5. Identification Strategy and Cross-Sectional Heterogeneity

A central challenge in estimating the effect of AI adoption on financing outcomes is endogeneity. Firms that adopt AI may differ systematically from non-adopters in ways that also affect their cost of capital—for example, in managerial quality, growth opportunities, or underlying risk. To address this concern, we combine an instrumental variables (IV) approach with cross-sectional heterogeneity tests that are implied by the conceptual framework.

Instrumental variables approach.

We exploit shocks to the *feasibility* of AI adoption that are plausibly exogenous to firms' short-run financing conditions. Specifically, we use instruments based on:

- Local AI labor supply shocks, capturing variation in the availability of AI-relevant human capital across regions and over time;
- Historical IT intensity, reflecting pre-existing technological complementarities that lower the cost of adopting AI but are predetermined with respect to current financing outcomes; and
- Policy or regulatory incentives for automation, which shift adoption incentives without directly affecting firms' required returns.

In the first stage, these instruments predict firm-level AI adoption. In the second stage, we estimate the causal effect of predicted AI adoption on financing outcomes, including costs of debt and equity, allowing these effects to vary with disclosure quality, perceived risk, and governance credibility.

Cross-sectional heterogeneity.

The framework generates clear predictions about where AI adoption should matter most for required returns. We therefore test for heterogeneous effects across economically meaningful dimensions:

- Asset-heavy versus asset-light firms, where longer-duration cash flows imply greater sensitivity of valuation and discount rates to changes in required returns;
- Stable versus cyclical industries, where downside risk and tail exposure differ systematically; and
- Debt versus equity markets, where monitoring, control rights, and downside risk are more salient.

Consistent with the model, we expect (i) stronger discount-rate effects of AI adoption in stable, asset-heavy firms, and (ii) stronger sensitivity to governance and downside-risk conditions in debt markets than in equity markets. These heterogeneity tests both sharpen identification and provide additional evidence that observed financing effects operate through the information, risk, and governance channels articulated in Section 3.

4.6. Descriptive Patterns and Identification Diagnostics

To motivate the empirical analysis and assess the plausibility of the identification strategy, we begin by documenting broad descriptive patterns that distinguish firms adopting AI from otherwise similar non-adopters. At this stage, the objective is not causal inference but rather to establish whether adopters differ systematically in operating performance, information environment, and financing outcomes in ways consistent with the framework developed in Section 3.

In simple comparisons, AI adopters tend to be larger, more IT-intensive firms with stronger operating performance. Relative to non-adopters, they exhibit higher operating cash flow per asset, higher EBITDA margins, and greater overall scale. These patterns are consistent with selection into AI adoption by firms that already possess complementary technological infrastructure and managerial capacity. Adopters also, on average, display higher-quality disclosure, suggesting that AI use often coincides with more sophisticated reporting and communication practices.

Importantly, despite these favorable operating characteristics, average financing outcomes do not differ markedly between adopters and non-adopters. Measures of the implied cost of equity and bond yield spreads are broadly similar across the two groups. Analyst forecast dispersion shows no uniform pattern: while some adopters experience reduced disagreement, others do not. Taken together, these descriptive facts underscore a central theme of the paper—namely, that improvements in operating performance associated with AI adoption do not mechanically translate into lower required returns. This observation motivates focusing on conditional effects via information, risk, and governance channels rather than unconditional average effects.

We next examine identification diagnostics underlying the difference-in-differences design. Event-time analyses indicate that, in the years leading up to AI adoption, there are no statistically detectable pre-trends in operating performance, information-environment measures, or financing outcomes. In particular, pre-adoption dynamics in operating cash flows, the implied cost of equity, bond yield spreads, and analyst forecast dispersion are statistically indistinguishable from zero. The absence of anticipatory movements suggests that AI adoption is not preceded by differential trends in outcomes that would confound post-adoption estimates, lending support to the parallel-trends assumption.

Baseline regressions reinforce the descriptive patterns. AI adoption is associated with economically meaningful improvements in operating performance—consistent with higher expected cash flows—once firm- and time-fixed effects are included. In contrast, average effects on required-return measures remain small, mixed, or statistically weak. Equity and debt financing outcomes show little unconditional response, and information-environment measures exhibit heterogeneity rather than a uniform improvement. These findings reinforce the idea that AI adoption primarily affects expected fundamentals, while its pricing implications depend on how markets interpret the associated uncertainty and control environment.

Finally, conditioning on governance reveals a markedly different pattern. When AI adoption interacts with measures of governance credibility—covering oversight, auditability, and transparency—the effects on required returns become more pronounced. Strong governance mitigates estimation risk and monitoring concerns, leading to lower analyst forecast dispersion and narrower bond yield spreads following adoption. These effects are especially salient in debt markets, consistent with creditors' heightened sensitivity to downside risk and control. For mature firms, valuation implications are driven primarily by changes in required returns rather than proportional cash-flow gains, highlighting the dominance of discount-rate effects when cash-flow duration is long.

In summary, the descriptive evidence and identification diagnostics align closely with the paper's conceptual framework. AI adopters outperform operationally, but average financing costs do not fall unless governance and disclosure render AI use credible and monitorable. These patterns justify the subsequent emphasis on governance-conditioned estimates and debt-market responses, and clarify why unconditional estimates of AI adoption's effect on the cost of capital may appear weak despite strong underlying mechanisms.

5. EMPIRICAL STRATEGY

This section outlines the empirical strategy used to test whether AI adoption lowers firms' required returns, or instead increases perceived uncertainty, and why effects differ across firms. The design combines a staggered-adoption event study (difference-in-differences) with cross-sectional interactions that capture pre-adoption governance and disclosure quality. The baseline comparison is between adopters and similar non-adopters within the same industry and time period; the key tests ask whether capital-market responses are stronger when AI use is more verifiable and oversight is more credible.

5.1. Sample Construction and Data Sources

We build a firm-year panel (and, where available, a firm-quarter panel) of publicly listed firms with accounting, market, and ownership data, matched to filings and earnings call transcripts. We require consistent coverage for the inputs used to construct cost-of-capital measures and drop observations with missing key variables. To improve comparability, we work within a common support region by trimming extreme observations on size and price and winsorizing continuous variables.

AI adoption timing and intensity are identified from verifiable disclosures in annual reports and earnings-call transcripts, complemented by technology-related filings and other objective sources. The adoption date is the first disclosure of operational deployment (not generic intent). Intensity measures capture the breadth and salience of AI deployment (*e.g.*, use across multiple functions and repeated, specific discussions over time).

5.2. Variable Definitions

AI adoption and intensity. The treatment indicator equals one in periods after a firm first discloses operational AI deployment. Where available, intensity measures capture scale, breadth, and continuity of use. Robustness tests tighten the definition by excluding boilerplate language and requiring repeated, specific mentions.

Cost of equity. The primary outcome is the implied cost of equity (ICoE), computed from prices and analysts' earnings forecasts using standard residual-income and dividend-discount implementations. We also examine equity beta and idiosyncratic volatility to separate changes in systematic exposure from changes in firm-specific uncertainty.

Cost of debt. Debt outcomes include bond yield spreads over matched benchmarks, loan spreads when available, and credit rating changes. These measures are especially informative about perceived downside risk and monitoring concerns, and therefore help assess whether AI-related tail risk or governance credibility is priced more strongly by debt holders.

Governance and disclosure. Governance is proxied by board independence and expertise, institutional ownership/monitoring, and audit-quality indicators. Disclosure quality is measured by the specificity and decision-relevance of AI-related governance disclosures (*e.g.*, validation, auditability, oversight structures), as well as broader disclosure attributes (*e.g.*, readability and forward-looking specificity). All moderators are measured prior to adoption to avoid post-treatment bias.

5.3. Identification and Baseline Specifications

Event-study / difference-in-differences. The main design is a staggered-adoption event study that traces dynamic effects around the first operational AI deployment. The specification includes firm- and time-fixed effects and controls for time-varying fundamentals; event-time coefficients provide a pre-trend diagnostic and the post-adoption response path.

The baseline specification (illustrative) is:

$$y_{i,t} = \sum_{k \neq -1} \beta_k \ \mathbf{1}\left(\text{EventTime}_{i,t} = k\right) + \gamma_i + \delta_t + \mathrm{X}'_{i,t}\theta + \varepsilon_{i,t} \quad (3)$$

Here, $y_{i,t}$ denotes a cost-of-capital measure (or an operating outcome) for a firm i in period t. The indicators $1(\text{EventTime}_{i,t} = k)$ trace event-time dynamics relative to the omitted baseline period $k = -1$. Firm fixed effects are captured by γ_i, time fixed effects by δ_t, and $\mathrm{X}_{i,t}$ is a vector of standard controls—including firm size, leverage, profitability, investment, and R&D intensity—as well as industry-by-time controls. The error term is denoted by $\varepsilon_{i,t}$.

Because staggered DiD can be biased under heterogeneous treatment effects, we replicate estimates using modern DiD estimators and alternative comparison groups (*e.g.*, within-industry not-yet-treated firms). Standard errors are clustered at the firm level and, where appropriate, two-way clustered by firm and time.

Interpretation. A decline in ICoE or credit spreads is interpreted as a reduction in required returns (discount rates). We read these results alongside operating performance to distinguish cash-flow improvements from discount-rate effects.

5.4. Governance and Disclosure as Moderators (Tests of H2)

To test heterogeneity, we interact AI adoption (or the event-time indicators) with pre-adoption governance and disclosure measures. The framework predicts that AI adoption lowers required returns when oversight and disclosure make AI use verifiable and downside risk credibly constrained, but that effects may be weaker-or even positive- when investors perceive higher model, control, or compliance risk.

We estimate an interaction event-study of the form, considering baseline specification with governance interactions:

$$y_{i,t} = \Sigma_{k \neq -1} (\beta_k + \varphi_k \cdot G_i) \cdot 1(\text{Event Time}_{i,t} = k) + \gamma_i + \delta_t + X_{i,t}'\theta + \varepsilon_{i.t} \quad (4)$$

where G_i is a pre-adoption governance or disclosure metric, the coefficients φ_k indicate whether firms with stronger governance and greater transparency exhibit different pricing dynamics in event time, before and after AI adoption, relative to less well-governed firms.

To reduce concerns that governance proxies mainly capture selection into adoption, we (i) condition on pre-adoption trends in outcomes, (ii) control for observable adoption incentives (*e.g.*, prior IT intensity, intangible assets, R&D), and (iii) implement matched-sample and reweighting analyses.

5.5. Debt-Market Tests (H3)

We estimate analogous event-study specifications for bond spreads, loan spreads, and rating changes. Because debt is more sensitive to downside tail risk and control, these tests provide a sharper read on whether AI adoption increases perceived crash risk, operational fragility, or governance concerns. Where data permit, we study heterogeneity by covenants, maturity, and secured status.

5.6. Mechanisms, Valuation Decomposition, and Nonlinearity (H4)

Mechanisms. We evaluate whether changes in required returns operate through (i) information risk (analyst disagreement, forecast errors, bid-ask spreads), (ii) perceived tail risk (skewness, downside beta, and option-implied measures where available), and (iii) governance credibility (monitoring intensity and audit-related outcomes). These tests are interpreted as mechanism-consistent evidence rather than as definitive evidence of mediation.

Valuation decomposition. To separate cash-flow news from discount-rate news, we examine valuation and return responses alongside standard cash-flow proxies (*e.g.*, profitability and growth revisions) and compare patterns across equity and debt markets.

Nonlinearity. We allow for concave or threshold effects in AI intensity by testing whether marginal benefits diminish at high intensity and whether risk effects emerge only beyond a deployment scale at which correlated failures or model risk become material.

5.7. Robustness, Falsification, and Alternative Explanations

Robustness checks include alternative definitions of adoption, alternative cost-of-capital measures, exclusion of industries experiencing confounding technology shocks, and placebo adoption dates. We also test for differential pre-trends, anticipation effects, and sensitivity to sample composition.

To address the concern that AI adoption proxies for managerial optimism or disclosure style, we control for general tone and forward-looking language, use non-AI technology disclosures as placebo treatments, and verify that results persist when restricting the treatment to verifiable operational deployments.

6. DISCUSSION

This paper begins with a simple, under-theorized corporate finance question: when firms adopt AI, do capital markets interpret it as a reduction in risk that lowers required returns, or as a new source of uncertainty that raises them? Our framework and evidence point to a conditional answer. AI adoption often improves operating performance, but its capital-pricing effects depend on whether outsiders can verify what the technology does, anticipate how it can fail, and trust the governance and controls that constrain it. In this sense, AI is not only an efficiency-enhancing input; it is also a belief-shaping technology that alters how investors map firm actions onto beliefs about cash-flow predictability, downside risk, and managerial control. Put differently, AI may boost the mean while thickening the tail.

6.1. Implications for Empirical Research

A central implication is that AI adoption should be treated as multidimensional rather than a single binary indicator. The same adoption event can raise expected cash flows while moving required returns in either direction, depending on disclosure and governance. This helps explain why unconditional “average effects” can be small even when underlying mechanisms are strong.

Several research directions follow:

1. Separate cash-flow news from discount-rate news.

Valuation responses to AI can reflect improved expected fundamentals, lower required returns, or both. Empirical designs should explicitly distinguish operating improvements from discount-rate changes—especially for mature firms where small shifts in required returns can dominate valuation.

2. Treat governance and disclosure as mechanisms, not nuisance controls.

If AI changes the credibility of the cash-flow-generating process, governance is not merely a firm characteristic to control for. Interaction tests (AI × governance/disclosure) are central for identifying when adoption reduces priced uncertainty versus when it increases it.

3. Use intermediaries as “belief sensors.”

Analyst disagreement, forecast errors, liquidity measures, and the speed of price discovery provide observable traces of belief updating. These outcomes help link adoption to required returns by altering information risk.

4. Distinguish adoption, intensity, and governance quality.

Binary indicators mask key variation. Intensity (scale/breadth) is likely most relevant for cash-flow outcomes; governance quality and disclosure specificity are more directly tied to discount-rate responses.

5. Exploit plausibly exogenous shifts in AI feasibility.

Endogeneity is unavoidable: firms adopt AI when conditions are favorable. Research designs that use plausibly exogenous variation in feasibility (*e.g.*, local AI skill supply, technology complements, policy incentives) can strengthen identification and clarify whether the governance-conditional patterns persist.

6. Expect stronger heterogeneity across markets and risk states.

Debt markets and stress regimes should price tail and control risks more sharply than equity markets in normal times. Designs that allow for state dependence are therefore especially informative.

Overall, the empirical message is not “test more outcomes,” but “test the right objects”: measures that capture how AI changes belief precision, downside exposure, and control credibility, not only mean performance.

6.2. Implications for Managers and Policymakers

For managers, AI adoption is not, by itself, a financing strategy. A firm can deploy AI to improve operations and still see little change in financing costs if capital providers cannot assess the extent of the change or whether the gains are durable. Financing benefits are more likely when AI investment is paired with decision-relevant disclosure and credible governance, such as:

- Specific disclosure: what processes AI affects, how performance is monitored, known failure modes, and how overrides work.
- Monitorable governance (not symbolic): model validation, audit trails, clear accountability for outcomes, and human oversight where warranted.
- Controls over third-party and data dependence: vendor risk management, data provenance, monitoring for drift and distribution shifts.

In practice, firms seeking lower-cost capital should treat AI governance as integral to the investment, rather than an afterthought.

For policymakers, standards can reduce uncertainty by improving comparability and verifiability, but they can also increase “compliance noise” if they induce boilerplate that does not improve measurability. Policy priorities include:

- Minimum governance expectations for validation, auditability, and accountability in high-stakes uses.
- Disclosure guidance that discourages boilerplate and pushes toward decision-useful specificity.
- Attention to concentration and correlated failures when many firms depend on similar models, vendors, or data sources—conditions under which AI can transmit shocks across firms and markets.

More broadly, AI’s pricing effects are not purely firm-specific: opacity and correlated dependence can spill into credit markets and, in extreme cases, into financial stability.

6.3. Implications for FinTech Firms

The framework has particularly sharp implications for FinTechs, where AI is often the core production technology rather than a complementary tool (Moro-Visconti, 2024). In digital lending, payments, fraud detection, robo-advisory, and algorithmic risk assessment, AI systems frequently determine credit allocation, pricing, and risk exposure directly, thereby intensifying information, tail risk, and governance channels.

Because many FinTech cash flows are effectively the output of a model—approval rules, fraud thresholds, and portfolio constraints—required returns are unusually sensitive to auditability, override authority, and regulatory credibility.

Information and estimation risk are structurally higher. FinTech cash flows are often produced by algorithmic decision rules rather than physical assets or stable operating routines. Outsiders, therefore, face greater difficulty in assessing persistence, scalability, and failure modes. As a result, performance improvements may be discounted as fragile unless the disclosure is unusually specific regarding the model's purpose, monitoring, validation, and oversight.

Risk transformation is more central. AI-driven scoring and automation can reduce idiosyncratic noise yet increase sensitivity to data shifts, feedback loops, and rare failures. Shared architectures, common data sources, and third-party vendors can also create correlated model errors, making FinTech AI risk look less diversifiable—especially during stress episodes.

Governance credibility carries outsized weight. In many FinTechs, AI does not merely assist humans; it can replace human judgment at scale. That magnifies concerns about accountability, override authority, regulatory compliance, and control. Debt investors, rating agencies, and regulators are therefore likely to place disproportionate weight on auditability, explainability, and human-in-the-loop safeguards.

Taken together, the framework predicts more extreme outcomes in FinTech. Well-governed FinTechs with transparent, auditable AI can earn substantial reductions in required returns because credible oversight sharply reduces estimation and monitoring costs. Conversely, opaque or weakly governed FinTechs may face higher capital costs than comparable firms—even when average performance is strong—because investors price tail and control risks more aggressively. This perspective helps rationalize the wide dispersion in FinTech valuations and financing conditions. It reinforces the paper's broader message: when AI sits at the center of value creation, capital pricing is driven less by efficiency gains alone and more by belief formation, risk perception, and governance credibility.

Eventually, this study offers several implications for the FinTech literature by identifying AI as a material financial technology with measurable effects on firms' cost of capital. The results suggest that AI-enabled financial technologies—such as algorithmic credit scoring, predictive risk analytics, and automated financial decision systems—can improve information efficiency and reduce uncertainty perceived by capital providers. These effects are consistent with the role of FinTech innovations in mitigating information asymmetries and enhancing market discipline.

Within the context of sustainable finance, the observed reduction in the cost of capital associated with AI adoption may support long-term value creation by facilitating access to financing for innovation-intensive and sustainability-oriented investments. AI-based tools can improve the quality, granularity, and timeliness of ESG-related information, thereby strengthening the integration of non-financial risks into capital allocation and risk pricing mechanisms.

Moreover, the findings highlight the relevance of FinTech governance and AI regulation as complementary factors shaping the financial outcomes of AI adoption. Effective governance frameworks that ensure transparency, explainability, and robustness of AI models may reinforce investor confidence and amplify the capital market benefits identified in this study. Overall, the results position artificial intelligence at the intersection of FinTech innovation and sustainable digital finance, with implications for both financial performance and the responsible adoption of technology.

8. CONCLUSION

This paper asks whether AI adoption lowers required returns or instead raises perceived uncertainty. The answer is conditional: AI often improves operational performance, but financing benefits arise only when outsiders can verify what the technology does, understand its failure modes, and trust the governance and control.

The key insight is that AI is not only a productivity tool but a capital‑pricing technology: it changes how investors map firm actions into beliefs about risk, information quality, and managerial discipline.

Consistent with the framework, operating outcomes tend to improve after adoption, whereas average effects on the cost of capital are weak, reflecting offsetting forces. Conditional benefits emerge when disclosure quality and AI governance are strong, particularly in debt markets and in mature firms, where changes in discount rates have outsized valuation effects.

Conceptually, the paper integrates technology, information, and governance into a unified mechanism for capital pricing, highlighting that what matters is not only adoption but observability, interpretability, and credible oversight. Our core contribution is to show that AI adoption is priced primarily through belief formation—via estimation risk, tail-risk perceptions, and governance credibility—so operating gains do not mechanically translate into lower required returns.

A natural limitation is that disclosure-based adoption measures may miss silent adopters; however, this is inherent to studies of emerging technologies, where observability is part of the mechanism.

Future work can refine identification and examine state dependence as AI systems become increasingly interconnected and standardized, potentially increasing correlated‑failure risk.

In sum, AI does not automatically buy cheaper capital; it buys potential that is realized when AI use is legible, auditable, and credibly controlled.

JEL Classification

G12; G32; M41; O33

Highlights

- AI is not merely an efficiency-enhancing input; it is a capital-pricing technology that reshapes how investors form beliefs about risk, information quality, and control.
- Improvements in operating performance from AI do not automatically translate into lower required returns; financing benefits arise only when AI adoption is predicted to reduce priced uncertainty.
- Governance and disclosure determine whether AI adoption lowers or raises the cost of equity and debt, helping explain heterogeneous capital-market reactions.

APPENDIX A. ILLUSTRATIVE TABLE TEMPLATES

The following tables are illustrative templates (expected patterns) used to clarify interpretation; they are not empirical results.

Table 2: Descriptive Differences between AI Adopters and Non-Adopters

Variable	AI Adopters	Non-Adopters	Difference
Operating cash flow/assets	Higher	Lower	+
EBITDA margin	Higher	Lower	+
Analyst forecast dispersion	Mixed	Lower	±
Implied cost of equity	Similar	Similar	n.s.
Bond yield spread	Similar	Similar	n.s.
Disclosure quality index	Higher	Lower	+
Firm size	Larger	Smaller	+
IT intensity	Higher	Lower	+

Table 3: Event-Study Lead Diagnostics (parallel trends)

Outcome	Leads (t = −3 to −1)	Interpretation
Operating cash flow	Not statistically different from zero	Supports parallel trends for performance
Implied cost of equity	Not statistically different from zero	No anticipatory repricing
Bond yield spread	Not statistically different from zero	No differential pre-adoption credit trend
Analyst forecast dispersion	Not statistically different from zero	No pre-adoption change in information environment

Table 9: Baseline effects of AI adoption
Panel A. Operating performance outcomes

Dependent variable	AI coefficient (expected sign)	Firm FE	Year FE
Δ Operating cash flow	+	Yes	Yes
Δ EBITDA	+	Yes	Yes
Δ Operating margin	+	Yes	Yes

Table 10: Governance-conditioned effects and valuation implications
Panel A. Governance interactions

Dependent variable	AI	AI × Governance	Interpretation
Implied cost of equity	Small / +	−	Governance lowers estimation risk.
Analyst forecast dispersion	Small / +	−	Transparency reduces uncertainty
Bond yield spread	Small / +	−	Credit markets reward credible oversight.

APPENDIX B FORMAL FRAMEWORK

This appendix formalizes the intuition presented in Sections 3–5 in a concise form.

B1. Economic Environment and Timing

Consider a mature, publicly traded firm operating in discrete time t = 0, 1, 2, …. At t = 0, the firm chooses whether to adopt AI-based decision systems. Let $A \in \{0,1\}$ denote adoption. Adoption is costly and not fully reversible in the short run. It affects both the level and the distribution of future cash flows. Capital markets are competitive and price securities based on available information and beliefs about risk, governance, and control.

B2. Cash-Flow Technology

Let revenues and operating costs depend on the adoption status A:

$$R_t(A), C_t(A) \quad (A.1)$$

Operating cash flow is:

$$OCF_t(A) = R_t(A) - C_t(A) \quad (A.2)$$

AI can increase revenue through improved forecasting, pricing, and personalization, and reduce costs through automation, predictive maintenance, and process optimization. Free cash flow to the firm is:

$$FCFF_t(A) = OCF_t(A) - CapEx_t(A) - \Delta NWC_t(A) \quad (A.3)$$

Assumption A1 (Cash-flow effect).

$$E[FCFF_t(1)] \geq E[FCFF_t(0)] \quad (A.4)$$

AI weakly increases expected free cash flows, but it may also change volatility, downside risk, or sensitivity to rare shocks.

B3. Discount Rates and the Cost of Capital

Let the weighted average cost of capital depend on adoption status:

$$WACC(A) = w_E \cdot k_E(A) + w_D \cdot k_D(A) \cdot (1 - \tau) \quad (A.5)$$

where $k_E(A)$ is the cost of equity, $k_D(A)$ is the cost of debt, and τ is the corporate tax rate. The framework in Section 3 implies that AI can move required returns through three channels:

- Risk estimation: whether AI improves or worsens the precision with which outsiders can forecast cash flows.
- Risk transformation: whether AI changes the shape of risk (*e.g.*, tail exposure, correlated failures, model/data shocks).
- Governance credibility: whether investors believe AI-driven decisions are constrained, auditable, and accountable.

Importantly, these channels can offset each other. Even if expected cash flows rise, required returns may not fall if risk estimation or tail concerns increase.

B4. Firm Value and a Counterfactual Decomposition

Firm value at t = 0 can be written in reduced form as:

$$V(A) = E[FCFF(A)] / WACC(A) \quad (A.6)$$

The counterfactual effect of adoption is:

$$\Delta V = V(1) - V(0) \quad (A.7)$$

A first-order approximation highlights the two mechanisms emphasized in the paper:

$$\Delta V \approx (1/WACC(0)) \cdot \Delta E[FCFF] - (E[FCFF(0)]/WACC(0)^2) \cdot \Delta WACC \quad (A.8)$$

The first term is the cash-flow channel (H1). The second is the discount-rate channel (H2–H4). Because value is convex in discount rates for long-duration cash flows, modest changes in WACC can dominate moderate operating improvements—especially in mature firms.

APPENDIX C. PROPOSITIONS AND MAPPING TO THE MAIN FRAMEWORK

The formal structure above yields three implications that map directly into the paper's conceptual framework and empirical hypotheses. First, holding discount rates fixed, AI adoption weakly increases firm value by boosting expected free cash flows, reflecting productivity, forecasting, and allocation improvements (the cash-flow channel). Second, AI adoption affects valuation only to the extent that it does not increase required returns. When AI adoption increases risk estimation, tail exposure, or monitoring costs, required returns may rise enough to offset cash-flow gains (the discount-rate channel). Third, for mature firms with long-lived cash flows, valuation effects are often driven more by changes in required returns than by proportional changes in operating performance. These implications correspond to Hypotheses H1–H4 and motivate the empirical focus on separating operating outcomes from capital-pricing responses.

APPENDIX D. NUMERICAL SENSITIVITY (ILLUSTRATION)

A simple illustration shows that modest changes in discount rates can outweigh moderate cash-flow gains for long-duration firms, thereby motivating the focus on required-return responses among mature adopters (H4). $E[FCFF] = 100 WACC = 8\% V_0 = 100/0.08 = 1{,}250 E[FCFF] = 105$

Cross-sectional Heterogeneity

The framework implies systematic heterogeneity in how AI adoption affects valuation and financing outcomes. In stable, asset-heavy firms, long cash-flow duration amplifies sensitivity to changes in required returns, making governance credibility particularly important for capital pricing. In cyclical or high-growth firms, operating improvements may be more salient, while discount-rate effects are noisier and more state-dependent. Across markets, debt holders are expected to respond more strongly than equity holders to perceived downside risk and loss of control, implying greater sensitivity of bond spreads and credit ratings to AI governance quality.

APPENDIX E. DEBT-MARKET IMPLICATIONS

From a creditor's perspective, the relevant question is not only whether AI improves average performance, but whether it introduces hard-to-monitor tail risk or weakens control. When AI adoption reduces downside exposure and is accompanied by strong monitoring and governance, bond spreads should narrow and credit ratings should improve. Conversely, when adoption increases opaque model risk, correlated failure exposure, or perceived loss of accountability, creditors may require higher spreads despite improvements in operating performance. Accordingly, the framework predicts that debt-market benefits from AI adoption arise primarily when governance mechanisms render AI-driven decision-making auditable and credible (Hypothesis H3).

APPENDIX F. LINK TO THE ESTIMATING EQUATIONS

The empirical specifications in Section 4 correspond directly to the formal framework. Equation (A.9) represents the baseline panel regression relating AI adoption to financing outcomes, while Equation (A.10) introduces governance interactions that capture the conditional effect of AI on required returns:

$$Y_{it} = \alpha + \beta AI_{it} + \gamma_i + \delta_t + X_{it}'\theta + \varepsilon_{it} Y_{it} = \alpha + \beta_1 AI_{it} + \beta_2 (AI_{it} \times Governance_{it}) + \gamma_i + \delta_t + \varepsilon_{\mathrm{it}}.$$

For required-return outcomes, the model predicts that the average effect of AI adoption (β_1) is small or ambiguous, while the interaction term (β_2) is negative when governance improves the observability, credibility, and control of AI-driven decisions.

APPENDIX G. HYPOTHESES SUMMARY

- H1: AI adoption increases expected cash flows.
- H2: AI adoption lowers the cost of capital only when disclosure quality and AI governance are strong.
- H3: Bond spreads decline, and ratings improve only when AI governance is credible.
- H4: For mature firms, valuation effects are driven more by required-return changes than by proportional EBITDA changes.

APPENDIX H. ELASTICITIES AND DOMINANCE REGIONS

Let baseline firm value be:

$$V = \frac{FCFF}{WACC} \quad (A.11)$$

Elasticities

Elasticity with respect to cash flows:

$$\varepsilon_{FCFF} = \frac{\partial V}{\partial FCFF} \cdot \frac{FCFF}{V} = 1 \quad (A.12)$$

Elasticity with respect to the cost of capital:

$$\varepsilon_{WACC} = \frac{\partial V}{\partial WACC} \cdot \frac{WACC}{V} = -\frac{FCFF}{WACC \cdot V} = -\frac{1}{WACC} \quad (A.13)$$

For typical mature firms with $WACC \in [6\%, 10\%]$, $| \varepsilon_{WACC} | \in [10,17]$, implying extreme sensitivity to discount rates.

APPENDIX I. DOMINANCE REGIONS

Let AI-induced changes be $\Delta FCFF$ and $\Delta WACC$.

Discount-rate effects dominate operating effects when:

$$\frac{\mathbb{E}[FCFF(0)]}{WACC(0)^2} | \Delta WACC | > \frac{1}{WACC(0)} \Delta \mathbb{E}[FCFF] \quad (A.14)$$

Equivalently:

$$| \Delta WACC | > \frac{\Delta \mathbb{E}[FCFF]}{\mathbb{E}[FCFF(0)]} \cdot WACC(0) \quad (A.\ 15)$$

This condition defines dominance regions in the $(\Delta FCFF, \Delta WACC)$ space, clarifying why small perceived risk reductions can outweigh sizable operating gains.

APPENDIX L. ECONOMETRIC ROBUSTNESS AND ALTERNATIVE IDENTIFICATION

Because AI adoption is endogenous, we subject the main findings to a battery of robustness checks to rule out selection, anticipation, and measurement-driven explanations. The central qualitative conclusion remains stable: operating performance improves on average, while financing benefits depend on governance credibility, as shown in Table **4**.

Table 4: Robustness and Identification Checks

Check	Implementation	Conclusion
Dynamic event study	Multiple leads/lags; joint tests of pre-trends	No evidence of anticipatory effects
Placebo adoption dates	Randomized pseudo-events for non-adopters	No comparable effects
Matched samples/reweighting	PSM, entropy balancing, coarsened exact matching	Conditional effects persist
Alternative AI measures	Indicator vs intensity; text-based vs hiring-based	Patterns robust to measurement
Alternative governance measures	Disclosure quality, auditability, internal controls, and committee oversight	Interaction remains key
Alternative cost-of-capital models	Multiple implied CoE models; alternative spread definitions	Results stable
Industry×year fixed effects	Absorb sectoral shocks and tech cycles	Not driven by industry trends
Instrumental variables	AI feasibility instruments (labor supply, IT intensity, policy incentives)	Supports causal direction; conditionality remains.

Notes: These checks are designed to address (i) non-parallel trends, (ii) endogenous adoption, (iii) omitted variables correlated with technology cycles, and (iv) measurement sensitivity in AI, governance, and required-return proxies.

APPENDIX M. VISUAL SUMMARY OF AI ADOPTION AND CAPITAL PRICING

This appendix provides a visual summary of the paper's conceptual framework.

Figure **A.1** illustrates how AI adoption reshapes key dimensions of capital pricing across alternative governance regimes. When governance and disclosure are credible, AI-driven operating improvements are accompanied by reductions in estimation risk and tail risk, translating into financing benefits. In contrast, under weak or opaque governance, efficiency gains coexist with elevated uncertainty, which constrains improvements in capital pricing.

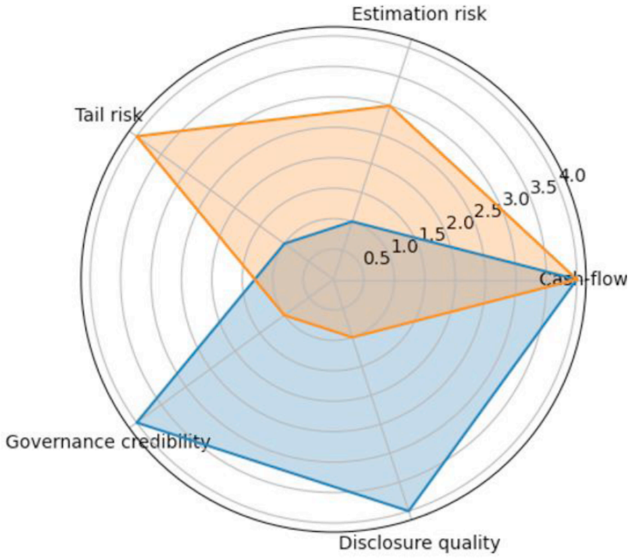

Figure A.1: Radar Chart.

APPENDIX N. CAPITAL-MARKET RESPONSES TO AI ADOPTION

Figure **A.2** presents an enhanced heatmap summarizing the predicted directional responses of key capital-market and risk variables to AI adoption across alternative governance regimes. The figure is intentionally qualitative and focuses on direction rather than magnitude.

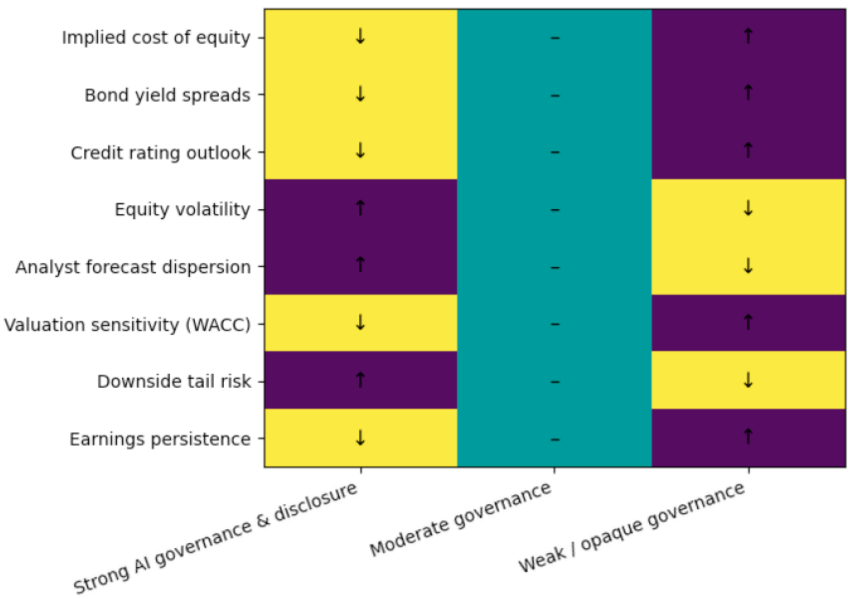

Figure A.2: Heatmap of AI adoption.

Legend: ↓ indicates lower perceived risk/required returns (*e.g.*, lower ICoE or narrower spreads); ↑ indicates higher; – indicates no first-order effect. The figure is qualitative and focuses on direction rather than magnitude.

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