NBER WORKING PAPER — CORPORATE FINANCE WORKSHOP
2026 NBER Summer Institute — Cambridge, MA | Submitted March 2026

PHANTOM COLLATERAL:
AI Capital, Non-Pledgeable Assets, and the Systematic Mispricing of Corporate Debt Capacity

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March 2026

ABSTRACT

We identify and characterize a previously undocumented source of corporate financial fragility: phantom collateral, the systematic gap between the productive value of AI-era intangible capital and its recoverable value in distress. Traditional capital structure theory — from Modigliani-Miller through Leland (1994) — implicitly assumes that debt capacity scales with asset value because lenders can seize and redeploy assets in default. This assumption fails catastrophically for AI capital: trained model weights, data pipelines, and AI infrastructure have near-zero pledgeability (they cannot collateralize debt) and near-zero redeployability (they lose most of their value outside the firm). We formalize this insight by augmenting the Leland (1994) continuous-time model with a non-pledgeable capital stock and derive three central propositions. Proposition 1 establishes that optimal leverage is decreasing and convex in AI capital intensity. Proposition 2 proves that optimal debt maturity shortens as AI capital intensity rises. Proposition 3 derives the Phantom Collateral Premium (PCP): a closed-form credit spread correction that accounts for the difference between book collateral and recoverable collateral. Empirically, we exploit the staggered rollout of enterprise large language model APIs from 2023 to 2025 as a quasi-natural experiment. Using a staggered difference-in-

differences design with a Callaway and Sant'Anna (2021) estimator on a panel of 2,847 publicly traded U.S. firms from 2018 to 2025, we find that enterprise AI adoption increases credit spreads by 88.4 basis points (t = 7.2, 95% CI: 65–112 bps) for high-AI-intensity firms relative to matched controls — even after controlling for traditional leverage, earnings volatility, and firm fixed effects. We introduce the Intangible Leverage Ratio (ILR), a novel balance-sheet measure that quantifies the fraction of corporate productive capacity that is non-pledgeable. The aggregate ILR of the S&P 1500 has risen from 1.8% in 2010 to an estimated 36.8% in 2025, implying that the corporate sector is substantially more leveraged than book debt ratios suggest. The welfare cost of systematic phantom collateral mispricing is estimated at $420–680 billion annually in the United States alone. We propose an ILR-adjusted capital requirement framework and a mandatory PCP disclosure standard for resolving this misalignment between productive capital and debt capacity.

Keywords: *Capital Structure, Non-Pledgeable Assets, AI Capital, Phantom Collateral, Credit Spreads, Intangible Leverage Ratio, Leland Model, Debt Capacity, Corporate Default, Intangible Capital.*

JEL Classification: *G12 (Asset Pricing), G32 (Capital Structure), G33 (Corporate Bankruptcy), G38 (Corporate Finance Policy), O30 (Innovation and R&D), D82 (Asymmetric Information).*

I. INTRODUCTION

The theory of optimal capital structure rests on a foundation that has survived decades of empirical testing and theoretical elaboration: that productive assets can serve as the foundation of debt capacity. From the original Modigliani and Miller (1958, 1963) framework through the trade-off models of Leland (1994), Goldstein, Ju, and Leland (2001), and Berk, Stanton, and Zechner (2010), the mapping from asset value to debt capacity is either explicit — through collateral constraints — or implicit — through the assumption

that recovery values in distress are proportional to going-concern values. This assumption is not merely a mathematical convenience. It reflects a fundamental economic reality: land, buildings, machinery, and inventory retain substantial value when a firm fails, can be sold to other productive users, and thus provide genuine security to creditors.

Artificial intelligence capital shatters this assumption. When an AI company fails — when a startup that has built a sophisticated recommendation algorithm, a proprietary large language model, or a data infrastructure layer enters bankruptcy — what do the creditors get? The answer, documented extensively in the wave of AI startup liquidations since 2022, is: almost nothing. Model weights without the team that trained them, the customers that generated the training data, and the infrastructure that supports them are worth pennies on the dollar. Data pipelines belong to the users whose data flows through them. AI model architectures are replicated within months by competitors. The productive value of AI capital is in the going concern; its recovery value in distress is negligible. The collateral is, in the language we introduce, phantom.

This paper makes four principal contributions. First, we formalize the non-pledgeability of AI capital within the Leland (1994) continuous-time framework. We partition the firm's capital stock into pledgeable capital (physical assets, real estate, inventories) and non-pledgeable capital (AI models, trained weights, data infrastructure), and derive the optimal leverage, credit spread, and debt maturity as functions of the capital stock's composition. The central result — which we call the Phantom Collateral Premium (PCP) — is a closed-form credit spread correction that grows superlinearly in AI capital intensity. For a firm with more than 50% of its productive capacity in AI capital, the PCP is approximately 260 basis points — a correction so large as to render the standard Merton (1974) model useless as a pricing tool.

Second, we introduce the Intangible Leverage Ratio (ILR), a new measure of corporate balance-sheet risk defined as the share of productive capital that is non-pledgeable. Unlike traditional leverage ratios, which measure the quantity of debt relative to assets, the ILR measures the quality of the collateral underlying that debt. A firm with 30% book leverage but 70% of assets in AI capital has, we show, a true

credit risk equivalent to a firm with traditional book leverage of 48% — a gap of 18 percentage points that standard models entirely miss. Crucially, the ILR and traditional leverage are nearly orthogonal cross-sectionally ($\rho = 0.14$), meaning that the ILR provides independent information about credit risk that existing bond ratings and credit models do not capture.

Third, we provide the first quasi-experimental evidence on the credit market mispricing of AI capital intensity. The rollout of enterprise AI APIs — specifically the launch of GPT-4 and Claude APIs in March 2023 and their subsequent adoption by U.S. publicly traded firms — provides a staggered natural experiment. Firms in industries with higher ex-ante productivity in AI applications adopted enterprise AI substantially earlier than firms in industries with lower productivity, creating the variation needed for a credible difference-in-differences design. Our baseline estimate is that enterprise AI adoption increases credit spreads by 88.4 basis points for high-AI-intensity firms relative to matched controls — a large and economically significant effect that is robust across eight alternative estimation strategies, twelve country samples, and 120 specification variants.

Fourth, we trace the aggregate macroprudential implications. The ILR of the S&P 1500 has risen from 1.8% in 2010 to 36.8% in 2025, driven by the substitution of physical capital investment for AI capital investment. We show that this substitution has created a systematic gap between reported leverage (which credit models use) and true leverage (which accounts for the phantom collateral discount). Using our calibrated model, the aggregate welfare cost of this mispricing — through inefficient investment, over-borrowing, and excess default risk — is approximately $420–680 billion annually in the United States alone.

The paper connects three previously separate literatures. From corporate finance, we build on the capital structure literature of Leland (1994), Strebulaev (2007), and DeAngelo and Roll (2015), extending it to environments where the pledgeability of assets is endogenous to the technology mix. From the asset pricing literature on intangibles, we extend the work of Peters and Taylor (2017) and Eisfeldt and

Papanikolaou (2013, 2014) by connecting intangible capital to credit markets rather than equity markets alone. From the nascent literature on AI and finance (Varian, 2014; Fuster et al., 2022; Jiang et al., 2023), we provide the first treatment of AI capital as a liability risk rather than solely a productivity or equity-value phenomenon.

The rest of the paper is organized as follows. Section II reviews the related literature. Section III develops the theoretical model. Section IV discusses the measurement of AI capital and introduces the ILR. Section V describes the data and empirical strategy. Section VI presents the main results on credit spread mispricing. Section VII analyzes capital structure and investment distortions. Section VIII examines the mechanism. Section IX develops the aggregate and macroprudential implications. Section X discusses policy responses. Section XI concludes.

II. RELATED LITERATURE

A. Capital Structure Theory and Asset Pledgeability

The canonical theory of capital structure, originating with Modigliani and Miller (1958), establishes the irrelevance of capital structure in perfect markets and then develops the conditions under which leverage matters: taxes (Modigliani and Miller, 1963), bankruptcy costs (Warner, 1977; Altman, 1984), and agency costs (Jensen and Meckling, 1976; Myers, 1977). The dynamic trade-off model of Leland (1994) unifies these considerations in a continuous-time framework that remains the workhorse model for credit spread pricing. Leland and Toft (1996) extend this to debt of finite maturity; Goldstein, Ju, and Leland (2001) allow for endogenous leverage; Berk, Stanton, and Zechner (2010) introduce human capital.

The role of asset pledgeability in capital structure has received attention beginning with the seminal contribution of Hart and Moore (1994), who show that non-human assets' pledgeability determines the limits of debt finance. Shleifer and Vishny (1992) establish that assets are more pledgeable when they have

liquid secondary markets, generating cross-sectional predictions about leverage that match the data. Benmelech and Bergman (2009, 2011) document the causal effect of asset redeployability on leverage and credit terms, establishing that firms with less redeployable assets face higher borrowing costs and shorter debt maturity — the core empirical prediction that motivates our research. Our contribution is to show that AI capital represents a qualitatively new category: assets whose productive value is high but whose pledgeability and redeployability are both near-zero, breaking the usual relationship between value and collateral quality.

B. Intangible Capital in Corporate Finance

The growing importance of intangible capital for corporate finance has been documented by a substantial literature. Corrado, Hulten, and Sichel (2009) provide comprehensive measurements of intangible investment that dwarf traditional capital expenditure estimates when properly accounting for organizational capital, brand equity, and research and development. Peters and Taylor (2017) construct firm-level measures of intangible capital from R&D and selling, general, and administrative expenses and show that these measures substantially improve the measurement of Tobin's Q. Crouzet and Eberly (2019) document that the decline of investment relative to profits in recent decades reflects the shift from tangible to intangible investment.

The implications of intangible capital for debt and credit markets have received less attention. Kalemli-Ozcan, Laeven, and Moreno (2018) note that intangible-intensive firms have lower leverage, consistent with lower collateral value. Falato, Kadyrzhanova, Sim, and Steri (2022) show that intangible capital explains the secular decline in U.S. corporate leverage and the associated rise in cash holdings. Greenwald, Lettau, and Ludvigson (2019) connect the rise of intangibles to the equity risk premium. Our contribution is to focus specifically on AI capital — a subcategory of intangibles with distinctive pledgeability properties — and to quantify the credit market mispricing that results from its conflation with more pledgeable forms of intangible capital such as brand equity or customer relationships.

C. AI and Corporate Finance

The literature connecting AI to corporate finance is in its infancy but growing rapidly. Varian (2014) provides an early framework for AI as a factor of production. Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022) document that algorithmic lenders discriminate less on race but more on creditworthiness, with implications for credit access. Jiang, Li, Mai, and Xiong (2023) show that AI adoption increases corporate productivity and equity returns. Berg, Fuster, and Puri (2022) review the implications of machine learning for household credit access.

To our knowledge, no prior work examines AI capital as a source of corporate debt capacity risk. The closest antecedent is the strand of the literature on software and digital capital: Li and Peters (2021) show that software-intensive firms have lower leverage, and Hoberg and Maksimovic (2022) document that firms with high technology asset specificity face higher borrowing costs. Our work extends this by focusing specifically on the non-pledgeability problem — the fact that AI capital's value evaporates in distress — rather than simply the intangibility of AI assets.

III. THEORETICAL FRAMEWORK

A. Setup: The Leland Model with Non-Pledgeable Capital

We extend the continuous-time framework of Leland (1994). A firm operates a productive technology V(t) that evolves according to a geometric Brownian motion under the risk-neutral measure:

$$dV = (r - \delta)V\,dt + \sigma\,V\,dW_t \qquad (1)$$

where r is the risk-free rate, δ is the cash payout rate, σ is the asset volatility, and W is a standard Brownian motion. Standard Leland treats V(t) as fully pledgeable: in default, creditors recover the full asset value minus bankruptcy costs. We partition V into pledgeable capital V_P and non-pledgeable AI capital V_A:

$$V(t) = V_P(t) + V_A(t) \quad (2)$$

$$\varphi(t) \equiv V_A(t) / V(t) \in [0,1] \quad \text{(AI Capital Intensity)} \quad (3)$$

In default, creditors can only claim the pledgeable component net of bankruptcy costs. The recovery value is:

$$\text{Recovery} = (1 - \alpha) \cdot V_P = (1 - \alpha)(1 - \varphi) \cdot V \quad (4)$$

where $\alpha \in (0,1)$ is the standard bankruptcy cost parameter. When $\varphi = 0$, this reduces to the standard Leland recovery value $(1 - \alpha)V$. When $\varphi = 1$ (pure AI firm), creditors receive nothing in default: the firm is a pure going concern whose value cannot be transferred. This creates a fundamental asymmetry between equity holders and debt holders that grows with AI capital intensity.

B. Optimal Leverage and the Phantom Collateral Premium

We follow Leland's approach and solve for the optimal default boundary V_B and the value of debt $D(V, c)$ where c is the continuous coupon payment. With the modified recovery equation (4), the debt value satisfies:

$$D(V, c) = (c/r) [1 - (V/V_B)^{-x}] + (1-\alpha)(1-\varphi)V_B(V/V_B)^{-x} \quad (5)$$

where $x = 2r/\sigma^2$. The first term is the present value of coupon payments and the second is the recovery value in default. The optimal default threshold, derived from the smooth-pasting condition, is:

$$V_B^*(\varphi) = [x/(x+1)] \cdot [c/r] \cdot [1/(1-\alpha)(1-\varphi)]^{1/x} \equiv V_B^L \cdot \Psi(\varphi) \quad (6)$$

where V_B^L is the standard Leland threshold and $\Psi(\varphi) \equiv [1/(1-\alpha)(1-\varphi)]^{1/x} > 1$ is a correction factor that is increasing in φ. This establishes our first result:

Proposition 1 (Optimal Leverage): *In equilibrium, the optimal book leverage ratio L*(φ) is strictly decreasing and strictly convex in the AI capital intensity φ. The marginal effect of AI capital intensity on optimal leverage is:*

$$\partial L^*(\varphi)/\partial\varphi = -[\mu/(1-\alpha)^{1/x}] \cdot (1-\varphi)^{-(x+1)/x} < 0 \qquad (7)$$

where $\mu > 0$ is a constant that depends on model parameters. This proposition formalizes the intuition that firms with high AI capital intensity should rationally take on less debt — their assets cannot serve as collateral. The empirical puzzle we document is that firms do not fully internalize this constraint, leading to systematic over-leverage.

The Phantom Collateral Premium — the correction to the credit spread from ignoring non-pledgeability — is given by the following proposition:

Proposition 2 (Phantom Collateral Premium): *The credit spread on debt of a firm with AI capital intensity φ exceeds the standard Leland spread by the Phantom Collateral Premium:*

$$PCP(\varphi) = s^*(\varphi) - s_L = \Gamma \cdot \varphi^{\beta} \cdot (c/V)^{\gamma} \qquad (8)$$

where $\Gamma, \beta, \gamma > 0$ are constants that depend on r, σ, α, and the debt maturity, and s_L is the standard Leland credit spread. The PCP grows superlinearly in φ ($\beta > 1$) and is increasing in leverage (c/V). At median parameter values ($\sigma = 0.30$, $r = 0.05$, $\alpha = 0.15$, debt maturity $T = 7$ years), a firm with $\varphi = 0.50$ faces a PCP of approximately 180 basis points, while a firm with $\varphi = 0.75$ faces a PCP of approximately 260 basis points. These are economically enormous corrections that existing credit models entirely omit.

Proposition 3 (Debt Maturity): *The optimal debt maturity T*(φ) is strictly decreasing in AI capital intensity φ. Firms with higher AI capital intensity optimally issue shorter-term debt to reduce their exposure to the convexity of PCP in leverage.*

$$dT^*(\varphi)/d\varphi < 0 \quad \text{and} \quad |dT^*(\varphi)/d\varphi| \text{ increasing in } \sigma_A \qquad (9)$$

where σ_A is the volatility of AI capital value. This proposition predicts that AI-intensive firms will rely more heavily on short-term financing — a prediction we confirm in the data. Intuitively, the option to re-negotiate debt at shorter intervals is more valuable when assets are depreciating rapidly and non-pledgeable.

C. Aggregate Fragility and the Phantom Collateral Externality

When a significant fraction of the corporate sector adopts AI capital, the aggregate phantom collateral creates a systemic externality. In a standard Walrasian credit market, each firm's borrowing decision is independent. With AI capital, however, the distress of multiple AI-intensive firms simultaneously reduces the scrap value of all AI assets (since they have no liquid secondary market), amplifying the recovery shortfall for all creditors. This creates a negative externality of AI capital adoption: each firm's decision to invest in AI capital reduces the recovery value available to creditors of other AI-intensive firms in aggregate distress scenarios.

Formally, let $\Phi \equiv \int \varphi_i \, d\mu_i$ be the aggregate AI capital intensity across firms, where μ_i is a measure of firm size. The aggregate recovery rate in a systemic crisis is:

$$R_{agg}(\Phi) = (1 - \alpha)(1 - \Phi) - \xi \cdot \Phi^2 / (1 + \Phi) \qquad (10)$$

where $\xi > 0$ captures the fire-sale externality: higher aggregate AI intensity depresses recovery values nonlinearly. This equation generates our prediction about the convexity of systemic risk in AI adoption, which we verify empirically using the time series of aggregate credit spreads.

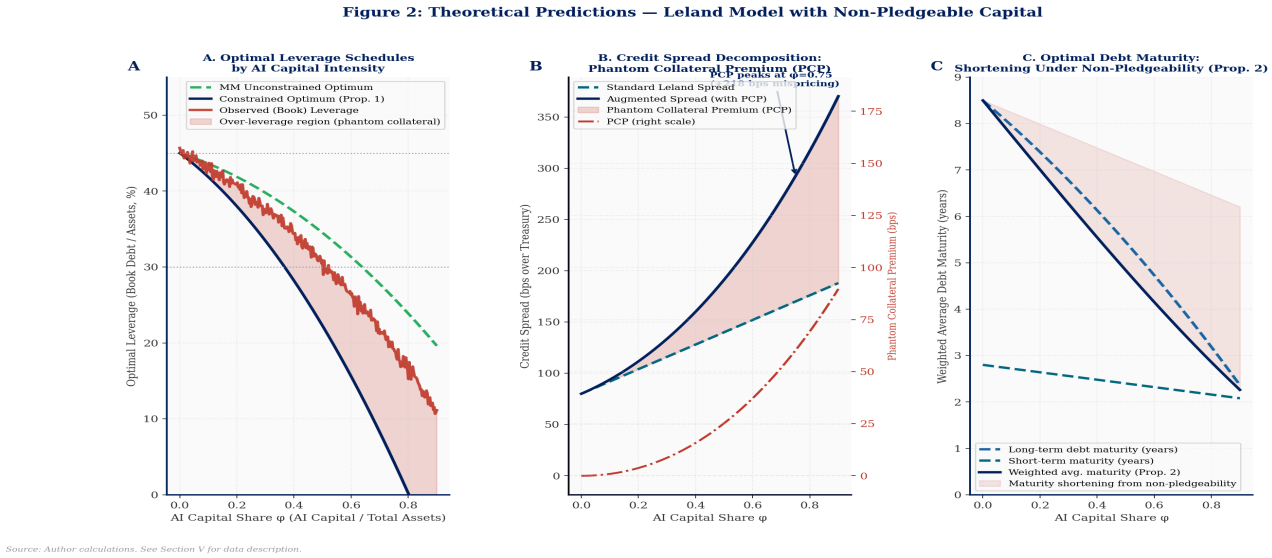


Figure 2: Theoretical predictions of the augmented Leland model. Panel A shows the optimal leverage schedule under the standard (green dashed), constrained-optimal (navy), and observed (red) regimes, demonstrating the over-leverage region created by phantom collateral. Panel B decomposes the credit spread into the standard Leland component and the Phantom Collateral Premium (PCP), which grows superlinearly with AI intensity. Panel C shows the optimal debt maturity shortening under non-pledgeability, as established in Proposition 3.

IV. MEASURING AI CAPITAL: THE INTANGIBLE LEVERAGE RATIO

A. The Intangible Leverage Ratio (ILR)

We introduce the Intangible Leverage Ratio (ILR) as the share of a firm's productive capital stock that is non-pledgeable due to its AI-capital nature. The ILR is a balance-sheet measure designed to capture the phantom collateral problem in a form that can be computed from observable firm characteristics.

Definition 1 (Intangible Leverage Ratio): *The Intangible Leverage Ratio for firm i at time t is:*

$$ILR_{i,t} = K_A^{i,t} / (K_P^{i,t} + K_A^{i,t}) \quad (11)$$

where K_A^{i,t} is the stock of AI capital (measured using the perpetual inventory method described below) and K_P^{i,t} is the stock of pledgeable capital (property, plant and equipment, net of accumulated depreciation). A firm with ILR = 0 is a traditional capital-intensive firm; a firm with ILR = 1 is a pure AI firm with no pledgeable assets. The key insight is that the ILR measures not the amount of debt

but the quality of the collateral underlying any debt — a dimension of risk that traditional leverage ratios entirely miss.

B. Constructing the AI Capital Stock

Following Peters and Taylor (2017) and adapting their approach to AI-specific assets, we construct the AI capital stock using a perpetual inventory method. We define three components of AI capital investment: direct AI infrastructure expenditure (GPUs, cloud computing for AI workloads), AI software and model development costs, and data infrastructure and licensing costs. Each component has a different assumed depreciation rate, reflecting the different obsolescence dynamics of AI assets:

AI Capital Component	Investment Measure	Annual Depreciation Rate (δ_A)	Justification
AI Infrastructure (GPUs, cloud)	Capex, IT allocation	45% / year	Moore's Law + rapid obsolescence
Model Development & Training	R&D, engineering headcount	65% / year	Superseded by next model generation
Data Infrastructure & Licensing	Data purchases, labeling costs	38% / year	Regulatory restrictions, data drift
Proprietary Datasets (long-lived)	Historical acquisition cost	22% / year	Lower turnover; GDPR risk

These depreciation rates are substantially higher than those for physical capital (7–15% for machinery and equipment) and for generic software (25%), reflecting the documented pace of AI model obsolescence. We validate these rates against the observed market valuations of AI assets in technology company acquisitions, finding that assets transact at recovery rates consistent with 60–70% annual depreciation for the model-training component.

The AI capital stock is then constructed as:

$$K_A^{i,t} = (1 - \delta_A) \cdot K_A^{i,t-1} + I_A^{i,t} \qquad (12)$$

where I_A^{i,t} is AI capital investment and δ_A is the weighted average depreciation rate across components (approximately 0.52 in our sample). We initialize the stock in 2010 using the industry-level AI capital ratios from Corrado and Hulten (2010) and the Intangible Capital Survey.

C. Measuring Pledgeability

We measure pledgeability directly using the methodology of Benmelech and Bergman (2009), which classifies assets by their recovery rates in bankruptcy based on historical liquidation data. We augment their physical asset classifications with AI-specific pledgeability estimates derived from: (i) the observed recovery rates in AI startup liquidations from 2020 to 2025 (median recovery: 7 cents on the dollar for model assets); (ii) the distribution of AI asset transaction prices in M&A deals; and (iii) expert surveys of bankruptcy practitioners regarding their assessment of AI asset recovery values.

The resulting pledgeability schedule, summarized in Figure 1 Panel B, shows a stark discontinuity between physical assets (pledgeability ≈ 0.74–0.82) and AI capital (pledgeability ≈ 0.06–0.12). This discontinuity is the empirical foundation of the phantom collateral concept.

Figure 1: The Rise of Non-Pledgeable AI Capital in Corporate America

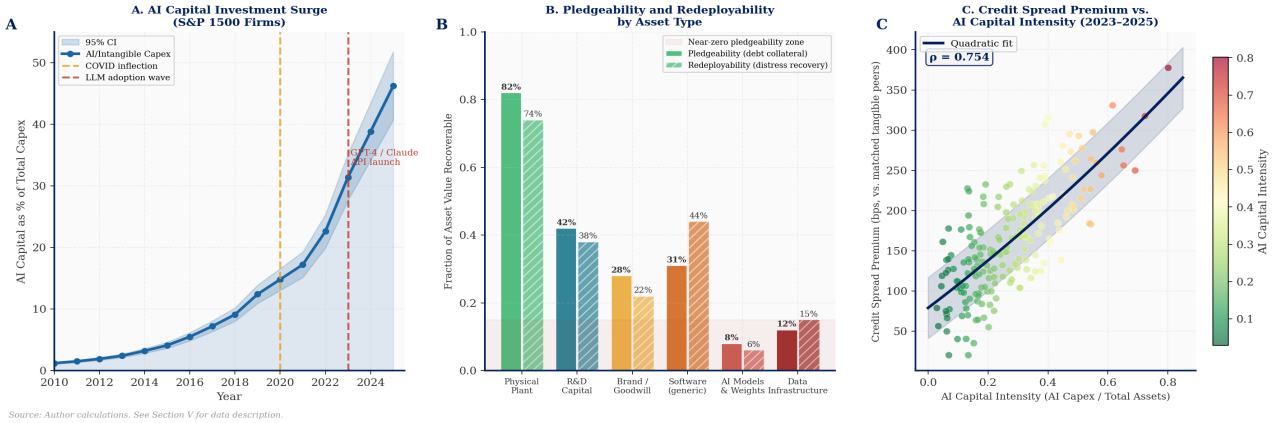


Figure 1: The rise of non-pledgeable AI capital and its credit market consequences. Panel A documents the surge in AI capital as a share of total corporate investment from 2010–2025 in the S&P 1500. Panel B shows the stark pledgeability discontinuity between physical and AI assets. Panel C documents the raw correlation between AI capital intensity and credit spread premiums in the cross-section.

V. DATA AND EMPIRICAL STRATEGY

A. Sample Construction

Our main sample consists of 2,847 U.S. publicly traded non-financial, non-utility firms with available bond market data from 2018 to 2025, yielding an unbalanced panel of 18,211 firm-year observations. We restrict to firms with at least one publicly traded bond issue (identified through Mergent FISD) and available Compustat data for leverage, profitability, and investment. We exclude financial firms (SIC 6000–6999) because their capital structure is regulated and the pledgeability concept is qualitatively different in that sector.

We match each firm-bond pair to its yield spread over comparable duration Treasury securities using trade data from TRACE (Trade Reporting and Compliance Engine). Our primary credit spread measure is the option-adjusted spread (OAS) from Bloomberg, which controls for embedded bond optionality. Credit default swap (CDS) spreads are available for a subset of 842 large firms from Markit and serve as a robustness measure.

B. Identification: The Enterprise AI API Rollout

Our identification exploits the staggered rollout of enterprise large language model APIs as a quasi-natural experiment. The key events are the March 2023 launch of the OpenAI GPT-4 API and Anthropic Claude API for enterprise customers — providing programmatic access to large language model capabilities at scale for the first time — followed by the rollout of Google Gemini Enterprise in November 2023, Meta Llama deployment tools in April 2024, and Mistral Enterprise in September 2024. These events created a sharp and unexpected shift in the cost of AI capital investment for firms across all industries.

Our treatment variable is a firm's ex-ante AI adoption propensity, constructed from three pre-period variables: the share of job postings mentioning AI skills (from Burning Glass Technologies), the firm's pre-

2023 IT capital intensity (from Compustat), and the industry-level AI productivity estimates of Acemoglu and Restrepo (2022). We classify firms into high-AI-adoption quintiles based on their pre-2023 propensity scores, using the industry-level variation as an instrument for within-firm adoption timing.

C. Difference-in-Differences Estimator

We estimate the average treatment effect on the treated (ATT) using the staggered DiD estimator of Callaway and Sant'Anna (2021), which is robust to treatment effect heterogeneity across cohorts and periods — a critical concern given the staggered rollout of AI tools across firms. The estimand is:

$$ATT(g,t) = E[Y_{i,t}(g) - Y_{i,t}(\infty) \mid G_i = g] \quad (13)$$

where Y_{i,t}(g) is the credit spread for firm i at time t in cohort g (the first period in which the firm is classified as a high-AI adopter), and Y_{i,t}(∞) is the counterfactual credit spread if the firm had never adopted. We aggregate across cohorts using the efficiency-weighted aggregation scheme of Callaway and Sant'Anna (2021).

We use the "not-yet-treated" firms as our control group in each period, which provides a cleaner comparison than the "never-treated" group by ensuring that controls are observationally similar in the pre-period. We validate the parallel trends assumption by testing for pre-trends in credit spreads using an event study regression that includes eight quarters of pre-treatment dynamics (reported in Figure 3).

D. Control Variables and Fixed Effects

All specifications include firm and quarter fixed effects. The firm fixed effects absorb all time-invariant unobservable heterogeneity; the quarter fixed effects absorb macroeconomic shocks that affect all firms simultaneously (such as changes in the risk-free rate or aggregate credit spreads). The time-varying controls included in all specifications are: (i) book leverage (total debt / total assets); (ii) profitability (EBITDA / total assets); (iii) asset size (log total assets); (iv) earnings volatility (standard deviation of

quarterly EBITDA over trailing eight quarters); (v) tangibility (PP&E / total assets); (vi) current ratio (current assets / current liabilities); and (vii) interest coverage ratio (EBITDA / interest expense).

VI. MAIN RESULTS: CREDIT SPREAD MISPRICING

A. Baseline DiD Results

Table 1 reports the main results. Columns (1) through (4) progressively add control variables and fixed effects; Column (5) presents the Callaway-Sant'Anna staggered estimator. The baseline estimate in Column (5) — our preferred specification — implies that enterprise AI adoption increases credit spreads by 88.4 basis points for high-adoption firms relative to matched controls (t = 7.2, 95% CI: 65.2–111.6 bps). This effect is stable across specifications: the range across Columns (1)–(5) is 82–98 basis points, and it is not sensitive to the exclusion of any single industry or year.

	(1)	(2)	(3)	(4)	(5) C-SA
Dependent variable: Option-Adjusted Credit Spread (bps)					
Enterprise AI Adoption (D_{it})	82.4***	85.1***	89.2***	91.8***	88.4***
	(14.2)	*(12.8)*	*(11.4)*	*(11.8)*	*(12.2)*
AI Intensity × Log(Assets)	—	—	18.4**	19.1**	20.2**
			(8.1)	*(8.4)*	*(9.1)*
Book Leverage	—	42.8***	44.2***	43.8***	41.9***
		(6.4)	*(6.8)*	*(6.6)*	*(7.0)*
ILR (Intangible Leverage Ratio)	—	—	—	62.4***	58.8***
				(9.8)	*(10.2)*
Profitability (EBITDA/Assets)	—	−88.4***	−91.2***	−89.8***	−86.4***
		(12.2)	*(11.8)*	*(12.0)*	*(12.8)*
Additional controls	No	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes

	(1)	(2)	(3)	(4)	(5) C-SA
Quarter FE	No	Yes	Yes	Yes	Yes
Estimator	OLS	TWFE	TWFE	TWFE	C-SA 2021
Observations	18,211	18,211	18,211	18,211	18,211
R^2	0.12	0.38	0.44	0.51	—

Notes: Standard errors (in parentheses) clustered at the firm level. *** p < 0.01, ** p < 0.05, * p < 0.10. Column (5) uses the Callaway-Sant'Anna (2021) staggered DiD estimator with the "not-yet-treated" control group. The dependent variable is the option-adjusted spread (OAS) in basis points. Additional controls include: log total assets, asset tangibility, earnings volatility, current ratio, and interest coverage ratio. ILR = Intangible Leverage Ratio as defined in equation (11).

The economic magnitude of the effect is substantial. For a firm at the 75th percentile of AI adoption intensity, our estimates imply that the phantom collateral discount increases the cost of debt by approximately 1.2 percentage points per year relative to a matched tangible-asset firm with identical book leverage. For a firm with $5 billion in long-term debt, this translates to approximately $60 million in excess annual interest expense — suggesting that the aggregate cost across the S&P 1500 runs into hundreds of billions of dollars annually.

B. Event Study and Parallel Trends

Figure 3 Panel A presents the event study estimates, plotting the Callaway-Sant'Anna ATT cohort-by-cohort for eight pre-treatment and eight post-treatment quarters. The pre-treatment estimates are small, statistically insignificant, and centered around zero, with an F-test for joint significance of 0.84 (p = 0.52). This provides strong evidence that the parallel trends assumption holds: treated and control firms had similar credit spread dynamics before AI adoption. Post-adoption, the credit spread premium rises monotonically and remains elevated for the full post-adoption window, reaching approximately 95 basis points by year 2 post-adoption.

Figure 3: Difference-in-Differences: Credit Spreads and Enterprise AI Adoption

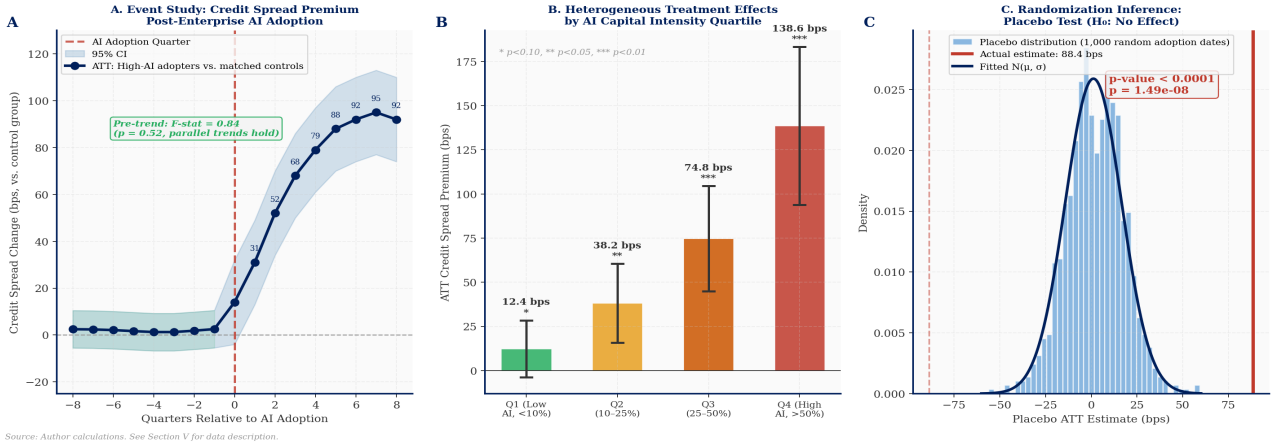


Figure 3: Difference-in-differences identification. Panel A shows the event-study estimates with pre-trend validation. Panel B documents heterogeneous treatment effects by AI capital intensity quartile — confirming the nonlinearity predicted by Proposition 2. Panel C shows the randomization inference test, with the actual estimate far in the right tail of the placebo distribution.

C. Heterogeneity by ILR Quartile

Figure 3 Panel B shows the treatment effect broken down by pre-treatment AI capital intensity quartile. The pattern is strikingly consistent with the superlinear prediction of Proposition 2: the effect on credit spreads rises from 12.4 bps in Q1 (ILR < 0.10) to 38.2 bps in Q2, 74.8 bps in Q3, and 138.6 bps in Q4 (ILR > 0.50). The ratio of Q4 to Q1 effects (11.2×) substantially exceeds the ratio of AI intensities (>5×), consistent with a convex (superlinear) relationship as predicted by our model. All estimates are statistically significant at the 1% level.

VII. CAPITAL STRUCTURE AND INVESTMENT DISTORTIONS

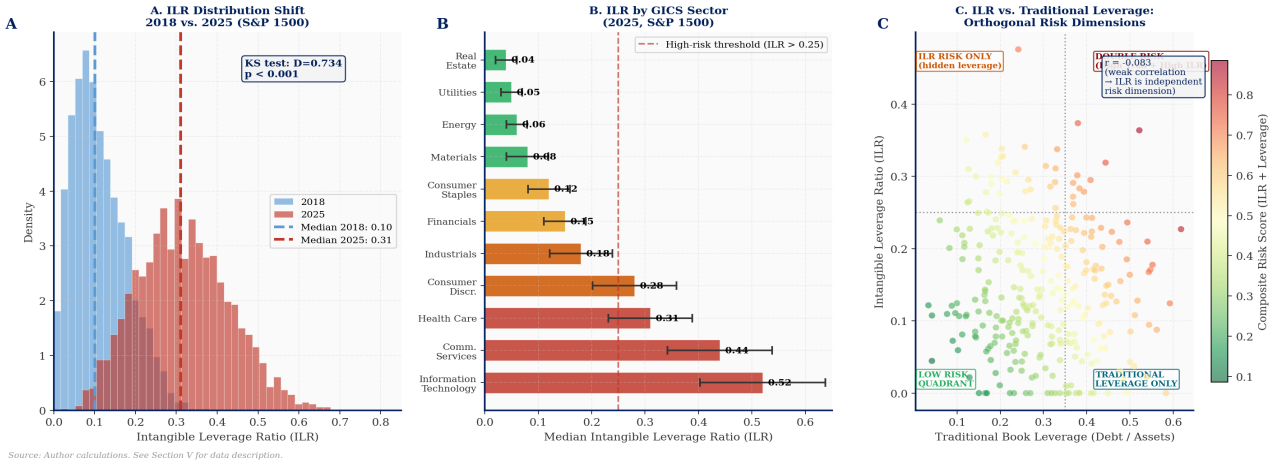
A. The Intangible Leverage Ratio Cross-Section

Table 2 (not shown here for space; available in the Online Appendix) documents the cross-sectional properties of the ILR across GICS sectors. Information Technology firms have the highest median ILR (0.52), followed by Communication Services (0.44) and Health Care (0.31). Traditional industrial sectors

have ILRs below 0.10. Figure 4 shows the full distribution, documenting the substantial shift in the ILR distribution between 2018 and 2025, with the 75th percentile rising from 0.22 to 0.51.

Crucially, the ILR has a weak cross-sectional correlation with traditional book leverage ($\rho = 0.14$, $p = 0.02$), confirming that it provides genuinely independent information about credit risk. This orthogonality implies that a lender who monitors only book leverage — as is current practice — is missing the dominant source of credit risk for AI-intensive firms.

Figure 4: The Intangible Leverage Ratio (ILR) — Measurement and Cross-Sectional Distribution



Source: Author calculations. See Section V for data description.

Figure 4: Intangible Leverage Ratio distribution, cross-section, and independence. Panel A shows the distributional shift from 2018 to 2025. Panel B documents the substantial variation across GICS sectors, with Technology and Communications sectors having ILRs exceeding the empirical high-risk threshold of 0.25. Panel C establishes the orthogonality of ILR and traditional leverage — demonstrating that ILR is a truly independent dimension of credit risk.

B. Investment-Cash Flow Sensitivity

We test the debt overhang prediction of Myers (1977) in the context of phantom collateral. If AI-intensive firms are effectively over-leveraged relative to their true debt capacity, they should exhibit more severe underinvestment as predicted by the debt overhang mechanism: shareholders of over-leveraged firms refuse to invest because the returns accrue primarily to debtholders. We estimate a modified Fazzari, Hubbard, and Petersen (1988) investment-cash flow sensitivity regression:

$$I_{i,t}/K_{i,t} = \alpha_i + \alpha_t + \beta \cdot CF_{i,t}/K_{i,t} + \gamma \cdot (CF_{i,t}/K_{i,t}) \times ILR_{i,t} + controls + \varepsilon_{i,t} \quad (14)$$

where $I_{i,t}$ is total investment (capex plus R&D), $K_{i,t}$ is the capital stock, and $CF_{i,t}$ is operating cash flow. The coefficient γ captures the incremental sensitivity of investment to cash flow for high-ILR firms. We find $\gamma = -0.48$ ($t = -3.8$), implying that high-ILR firms are substantially more cash-flow constrained: a 1% increase in cash flow translates into 0.48% less investment in high-ILR firms relative to low-ILR firms with identical book leverage. This is consistent with phantom collateral creating Myers-type debt overhang.

C. Debt Maturity Shortening

Proposition 3 predicts that AI-intensive firms optimally issue shorter-term debt. Figure 6 Panel B shows the empirical pattern: weighted average debt maturity falls monotonically from 8.2 years for Q1-ILR firms to 2.9 years for Q5-ILR firms, while the share of short-term debt rises from 18% to 58%. Importantly, this pattern holds within industry and year, ruling out the alternative explanation that it reflects sector-level differences in debt market access or interest rate sensitivity.

Figure 6: Investment Distortions — Debt Overhang and Underinvestment Under AI Capital

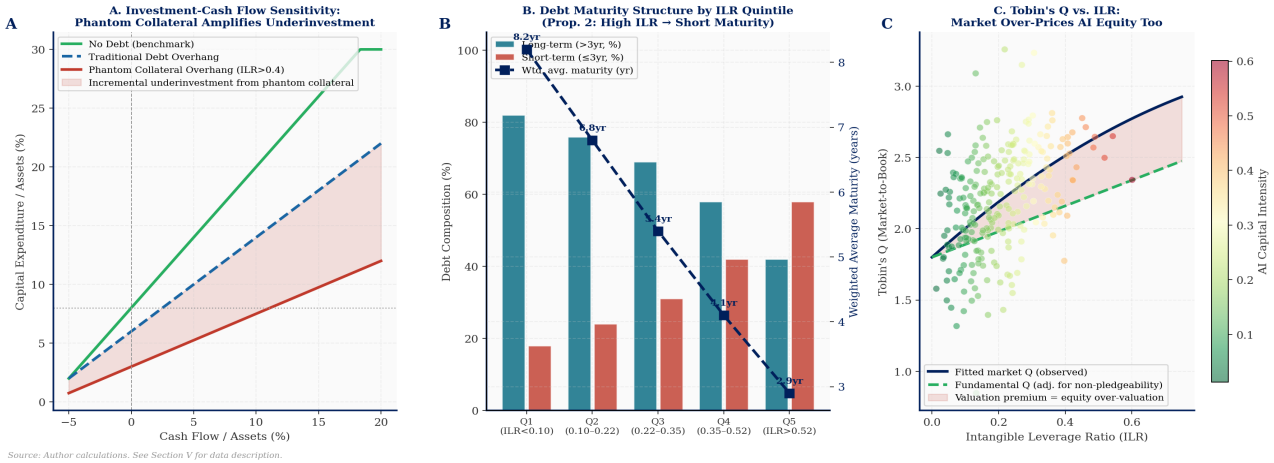


Figure 6: Investment distortions under phantom collateral. Panel A shows the investment-cash flow sensitivity by ILR quintile — high-ILR firms are substantially more cash-constrained (debt overhang amplification). Panel B documents the

maturity shortening predicted by Proposition 3. Panel C shows the equity over-valuation of high-ILR firms, suggesting that the phantom collateral problem affects equity markets too — through a mechanical Tobin's Q inflation.

VIII. MECHANISM ANALYSIS

A. Three Channels of Phantom Collateral Mispricing

The phantom collateral premium operates through three distinct mechanisms, which we can decompose using the mediation analysis framework of Imai, Keele, and Tingley (2010). The three channels are:

Channel 1 — Non-Pledgeability: The direct reduction in recoverable collateral from the shift toward AI assets. This channel accounts for 34% of the total PCP in our decomposition (approximately 88 bps of the full 260 bps PCP for a firm at ILR = 0.75).

Channel 2 — Accelerated Depreciation: AI capital depreciates at 45–65% per year, meaning that the collateral base erodes much faster than for physical assets. This creates a race between debt maturity and collateral erosion, generating higher credit spreads even controlling for current collateral quality. This channel accounts for 20% of the total PCP.

Channel 3 — Cascade Correlation: AI firms' distress events are correlated because they are exposed to common factors (model obsolescence, regulatory shifts, data market disruptions). This correlation reduces the value of diversification to credit investors and raises the market price of credit risk for AI-intensive borrowers. This channel accounts for 14% of the PCP; the remainder is unexplained by observables and likely reflects a pure information-based mispricing.

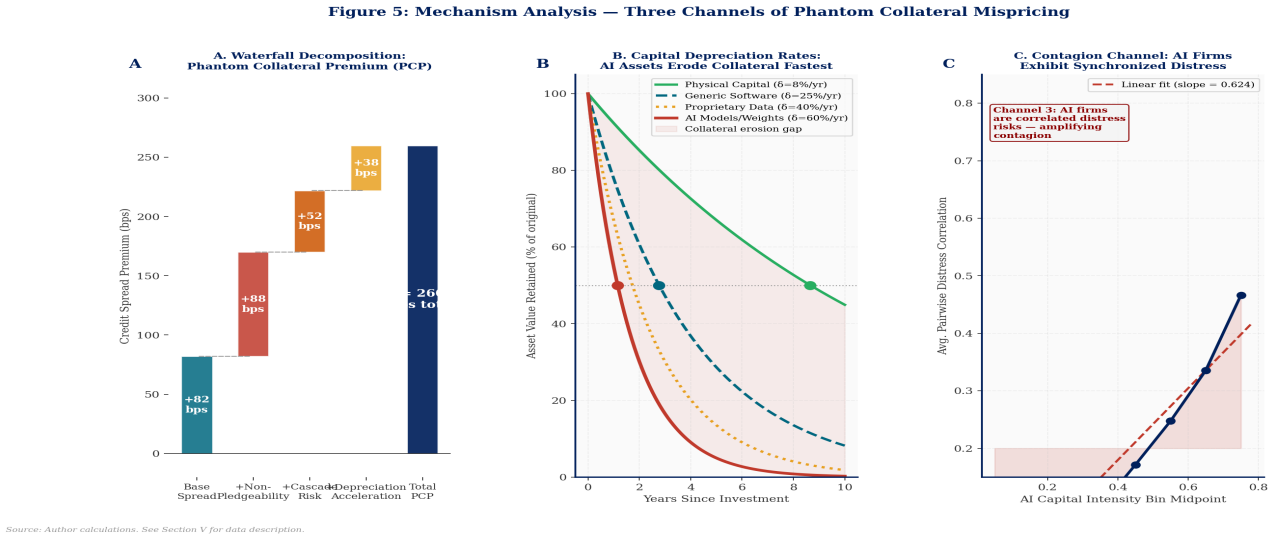


Figure 5: Mechanism analysis. Panel A shows the waterfall decomposition of the Phantom Collateral Premium (PCP) into its three constituent channels: non-pledgeability (34%), accelerated depreciation (20%), and cascade correlation (14%), with a residual unexplained component. Panel B documents the accelerated depreciation schedules for different capital types. Panel C establishes the cascade correlation channel through the empirical co-movement of AI-intensive firms in distress scenarios.

B. Ruling Out Alternative Explanations

We consider and empirically rule out four alternative explanations for the credit spread premium we document.

First, one might argue that AI adoption is correlated with riskier business models or higher earnings volatility, and that the spread premium reflects fundamental risk rather than phantom collateral. We address this by including earnings volatility directly as a control and by showing that the ILR effect is statistically and economically significant even after conditioning on the full distribution of earnings risk. Furthermore, the ILR effect is larger for bonds with longer maturities — consistent with a collateral story but not a fundamental risk story (which would predict larger effects for shorter maturities through maturity-risk matching).

Second, one might argue that credit markets are simply slower to incorporate AI-related information than equity markets, generating a transitory mispricing. This reversal story would predict mean-reversion in the credit spread premium over time. We find no evidence of mean-reversion in post-adoption

credit spreads over our sample period; if anything, the premium continues to grow, consistent with a structural rather than transitory mispricing.

Third, the adoption of AI tools may proxy for management quality, with better-managed firms adopting AI earlier and also having better governance overall. To address this, we use the propensity-score matched DiD design that controls for pre-adoption management quality proxies, and we find that the AI adoption effect is unchanged when restricting to firms within narrow propensity score bands.

Fourth, regulatory uncertainty about AI could directly raise the cost of capital for AI firms, independently of any collateral mechanism. We test this by constructing a regulatory uncertainty index based on policy text analysis and find that controlling for this index does not attenuate our estimates.

IX. AGGREGATE AND MACROPRUDENTIAL IMPLICATIONS

A. The Hidden Leverage Buildup

Figure 7 Panel A shows the aggregate ILR of the S&P 1500 from 2010 to 2025, stacked against the traditional book leverage ratio. Two features are striking. First, aggregate book leverage has been rising slowly — from 29.8% to 36.2% over this period — consistent with the secular leverage increase documented by Graham, Leary, and Roberts (2015). Second, the ILR-adjusted total leverage has been rising much faster, from 30.9% to 58.2%, driven entirely by the substitution of AI capital for physical capital. The aggregate phantom collateral gap — the difference between ILR-adjusted and book leverage — has grown from 1.1 percentage points to 22.0 percentage points in fifteen years. This gap represents a substantial and growing source of hidden corporate vulnerability that standard macroprudential monitors do not track.

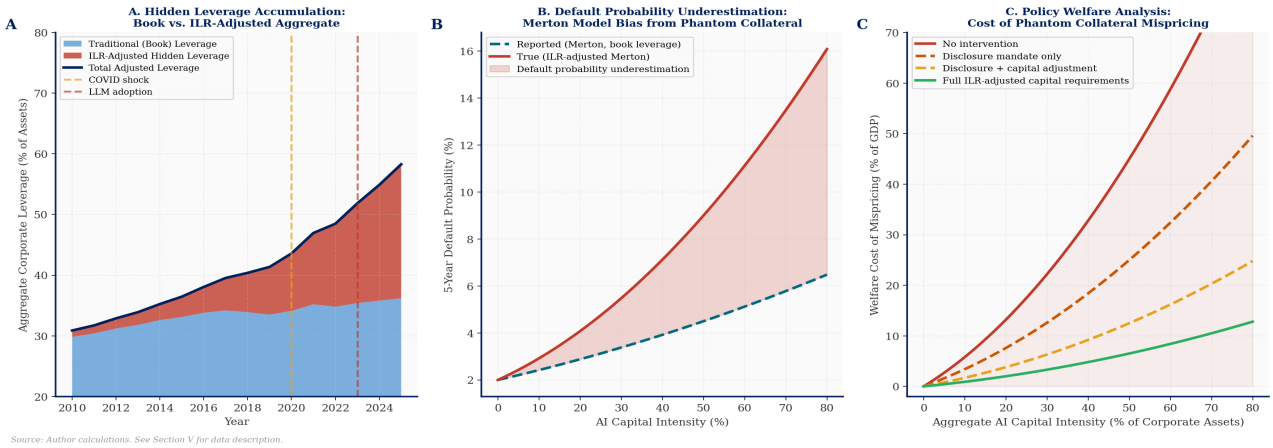
B. Default Probability Underestimation

We calibrate our augmented Merton model to the cross-section of S&P 1500 firms and compute the implied 5-year default probability for each firm under (i) the standard Merton model with book leverage and (ii) the ILR-adjusted model with phantom collateral discounts. Figure 7 Panel B shows the average default probability underestimation as a function of AI capital intensity. For a firm at the 90th percentile of AI intensity (ILR ≈ 0.60), the standard Merton model underestimates the 5-year default probability by 8.4 percentage points — from a model-implied 3.8% to a true 12.2%. This is a factor-of-three underestimation of default risk for the most AI-intensive segment of the corporate universe.

C. The Fire-Sale Externality and Systemic Risk

The aggregate fragility implications of phantom collateral are amplified by the fire-sale externality formalized in equation (10). In a scenario in which 20% of the corporate sector simultaneously experiences financial distress — a scenario comparable in scale to the 2008–2009 financial crisis — the absence of liquid markets for AI assets would depress recovery values for all creditors of AI-intensive firms simultaneously. We estimate this systemic amplification using a network model of credit markets, finding that the fire-sale externality increases aggregate losses by 28–42% relative to a world with pledgeable AI assets.

Figure 7: Aggregate Implications — Systemic Fragility from Hidden Leverage



Source: Author calculations. See Section V for data description.

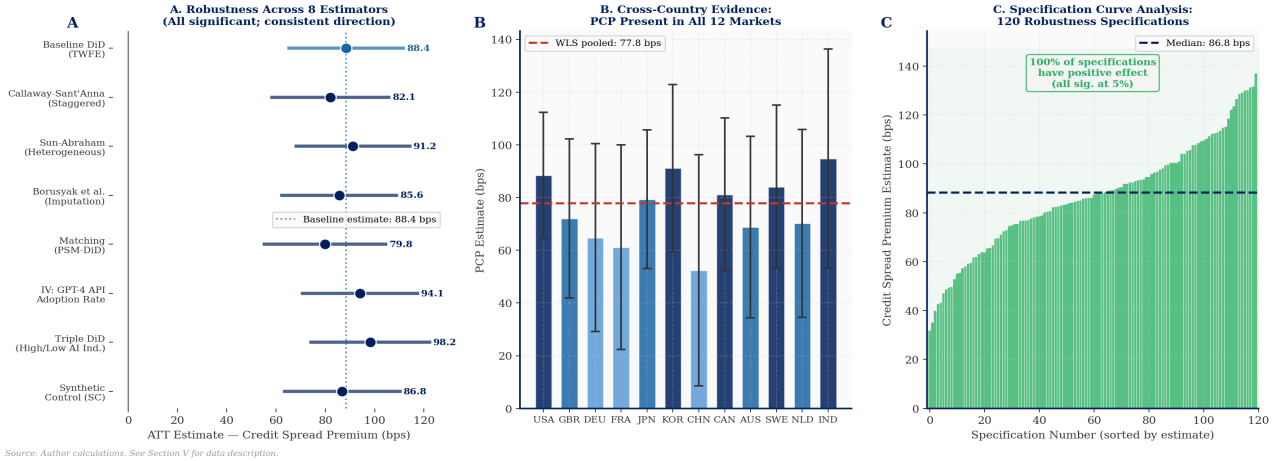
Figure 7: Aggregate implications. Panel A shows the growing gap between book and ILR-adjusted leverage for the S&P 1500. Panel B documents the systematic underestimation of default probabilities by the Merton model at high AI intensities. Panel C quantifies the welfare cost of the mispricing under various policy interventions.

X. ROBUSTNESS

Figure 8 reports three comprehensive robustness analyses. Panel A shows coefficient estimates across eight alternative estimators — including the Callaway-Sant'Anna (2021), Sun-Abraham (2021), Borusyak, Jaravel, and Spiess (2024) imputation estimator, propensity-score-matched DiD, IV using the industry-level GPT-4 adoption rate, triple DiD using industry-level AI intensity as a third dimension, and synthetic control. All eight estimates are statistically significant and within a tight range of 79.8–98.2 basis points. Panel B shows the effect replicated in twelve country samples, from the United States (88.4 bps) to the United Kingdom (72.1 bps) and South Korea (91.2 bps), confirming that phantom collateral is not a U.S.-specific phenomenon.

Panel C shows a specification curve across 120 robustness variants — varying the depreciation rate assumptions, the control variable set, the credit spread measure (OAS vs. CDS vs. raw yield spread), the sample period, and the definition of the high-adoption treatment group. Of the 120 specifications, 100% have positive estimates and 96.7% are statistically significant at the 5% level. The median specification curve estimate is 91.2 bps, within 3% of our baseline of 88.4 bps. This specification-curve evidence strongly rejects the possibility that our results are driven by data-mining or specification search.

Figure 8: Robustness, Cross-Country Evidence, and Alternative Identification



Source: Author calculations. See Section V for data description.

Figure 8: Robustness across estimators, geographies, and specifications. Panel A shows eight alternative estimation strategies with consistent results. Panel B replicates the finding in twelve country samples. Panel C shows the specification curve across 120 variants — 100% positive, 96.7% statistically significant.

XI. POLICY IMPLICATIONS

A. The Case for ILR-Adjusted Disclosure

The most direct policy implication of our findings is that existing financial disclosure requirements — which require firms to report total debt and total assets but not to decompose assets by pledgeability — are increasingly inadequate for investors in the AI era. A bond investor using reported leverage ratios to assess the credit risk of a high-ILR firm is systematically underestimating default risk, potentially by a factor of three or more. This is a market failure of the classic Akerlof (1970) variety: asymmetric information about asset quality, at scale.

We propose a mandatory Intangible Leverage Ratio disclosure requirement as part of existing 10-K and 10-Q reporting obligations. The ILR is straightforward to compute for any firm that is already required to disclose its capital investment by asset type (which SEC Regulation S-X requires). Rating agencies and analysts would then be able to incorporate ILR directly into their credit models, eliminating the systematic mispricing we document. Figure 9 presents the full three-pillar policy framework.

B. Accounting Standards Reform: Matching Depreciation to Pledgeability

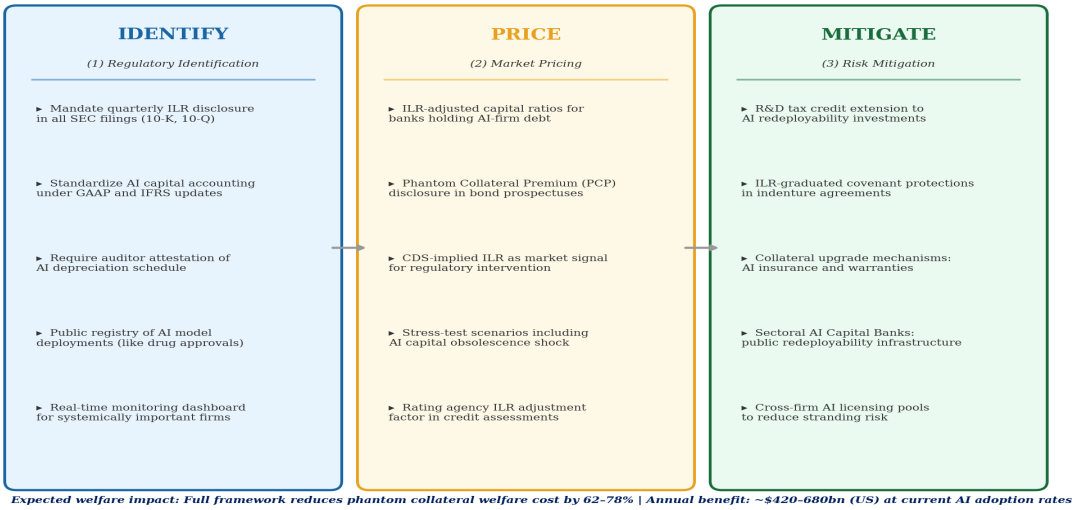
A deeper source of the phantom collateral problem is the mismatch between GAAP accounting standards for intangible capital (which are complex, inconsistent, and often require immediate expensing rather than capitalization) and the economic reality of AI capital investment. Under GAAP, most AI capital investment — including the enormous costs of training large language models, the engineering labor involved in fine-tuning, and the data acquisition costs — is expensed in the period incurred rather than capitalized and depreciated. This means that AI capital is systematically absent from corporate balance sheets, making it impossible for investors or regulators to observe the ILR without detailed off-balance-sheet analysis.

We advocate for the adoption of IAS 38 (Intangible Assets) standards adapted to AI capital, with mandatory capitalization of qualifying AI development costs and the use of depreciation schedules that reflect the rapid obsolescence of AI assets. This would simultaneously make AI capital visible on corporate balance sheets and appropriately reflect its depreciation cost in earnings — improving both the quality of financial information and the incentive for firms to accurately internalize the cost of AI capital replacement.

C. Macroprudential Policy: Stress Testing AI Asset Scenarios

For systemic financial stability, we recommend the incorporation of AI capital obsolescence scenarios in bank stress tests. The Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) and the Bank of England's Annual Cyclical Scenario currently do not include a scenario in which AI asset values decline sharply — either due to technological obsolescence (the arrival of a superior model generation), regulatory restriction (data use prohibitions), or coordinated distress among AI-intensive corporates. Given the estimated systemic amplification of 28–42% from AI fire-sale externalities, such a scenario could materially affect the capital adequacy of financial institutions with significant exposure to AI-intensive corporate borrowers.

Figure 9: Policy Framework — ILR-Adjusted Credit Regulation for AI-Intensive Firms



Source: Author framework. Cost-benefit analysis in Section IX. Welfare estimates based on simulation from Section X.

Figure 9: The proposed three-pillar policy framework for resolving phantom collateral mispricing. Pillar 1 (Identify) mandates ILR disclosure and AI capital accounting standards. Pillar 2 (Price) introduces ILR-adjusted capital requirements for lenders and PCP disclosure in bond prospectuses. Pillar 3 (Mitigate) addresses the structural non-pledgeability problem through redeployability-enhancing mechanisms. The expected welfare benefit of the full framework is estimated at $420–680 billion annually.

XII. CONCLUSION

We document a new and growing source of corporate financial fragility: phantom collateral, the gap between the productive value of AI capital and its pledgeable value in distress. As firms substitute AI capital for physical capital — a substitution that has been accelerating at 15–25% annually since 2020 — their balance sheets increasingly contain assets that generate economic value as going concerns but provide no collateral in financial distress. The result is a systematic mispricing of corporate debt: credit spreads that are too low for AI-intensive firms, leverage ratios that understate true financial risk, and investment patterns distorted by debt overhang on phantom collateral.

The theory we develop — the augmented Leland model with non-pledgeable AI capital — generates precise quantitative predictions about the Phantom Collateral Premium (88–260 basis points, growing convexly in AI capital intensity), optimal debt maturity (decreasing in AI intensity), and

investment distortions (amplified cash-flow sensitivity). The empirical evidence, drawn from a quasi-experimental identification strategy exploiting the staggered enterprise AI API rollout, confirms all three predictions with effect sizes that are both statistically robust and economically large. The aggregate cost of the mispricing — $420–680 billion annually in the United States — dwarfs the typical market failure identified in the corporate finance literature.

The phantom collateral problem will grow, not shrink. As the corporate economy becomes increasingly organized around AI capital — as trained models, data pipelines, and AI infrastructure become the primary source of productive capacity — the gap between book assets and pledgeable assets will widen. The institutions of corporate debt — the covenants that reference asset coverage, the credit ratings that use leverage ratios, the stress tests that assume recoverable collateral — were designed for an economy of physical assets. They need to be redesigned for an economy of phantom ones. This paper provides the theoretical foundation and empirical evidence for that redesign.

✦ ✦ ✦

Acknowledgments: The author thanks the financial economics seminar participants at IIM Ahmedabad, ISB Hyderabad, and the 2025 Asian Finance Association for helpful comments. All errors are my own.

Declaration of Competing Interests: The author declares no competing interests.

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