Financial Distress Risk and Intangible Asset Portfolio: Does Industry Standardization Matter?

Lei Sze Wing, Sharon
University of Warwick, Department of Economics
Supervisor: Professor Pablo Beker

September 10, 2025

Abstract

This dissertation examines the relationship between intangible asset portfolios and financial distress risk, focusing on whether industry-standardization of intangible capital reduces industry-specific risk exposure. Motivated by the theoretical framework of Maksimovic and Zechner (1991) and the empirical insights of MacKay and Phillips (2005), the study develops a three-equation system model capturing the joint dynamics of leverage, cash flow volatility, and intangible positioning. Using panel data on over 2,400 firms in the North America between 2000 and 2024, intangible alignment is measured through a PCA-derived index constructed from R&D intensity, identifiable intangibles, and total intangible assets. The results show that firms closer to the industry's technological core do not consistently exhibit lower cash flow volatility, although the direction of effect is theoretically consistent. Interaction models suggest that tangible assets do not significantly mediate the leverage effects of intangible alignment. These findings contribute to the literature on financial structure by highlighting the limited hedging role of standardized intangibles under current accounting conditions and underscoring the complexity of financing constraints in the intangible economy.

Contents

1 Introduction **4**

2 Literature Review **5**

2.1 Intangible assets, firm performance, and valuation 5

2.2 Financial distress risk and capital structure 6

2.3 The Classical Industry equilibrium models 6

2.4 Intangibles and Corporate Finance 7

3 Theoretical Model **8**

3.1 Output-realization Model 9

3.2 Financial Structure, Risk-Shifting, and Distress 12

3.2.1 The Industry Equilibrium Distribution 12

3.2.2 The Riskiness of Project Cash Flows 12

3.2.3 The Asset Substitution Channel 13

4 Data and Methodology **14**

4.1 Sample selection 14

4.2 Proxies and key variables 15

4.2.1 Financial Distress Risk 15

4.2.2 Intangible Portfolio 16

4.3 Empirical model specification 19

5 Results **20**

5.1 Descriptive Statistics 20

5.2 Baseline GMM Estimates OLS Comparison 21

5.2.1 Determinants of Leverage 21

5.2.2 Determinants of Cash Flow Volatility 23

5.2.3 Determinants of Intangible Portfolio 23

5.2.4 Robustness Check 23

5.3 Role of Collateral Capacity in Mediating Leverage–Risk Link 25

6 Conclusion **25**

1 Introduction

The transition to an information-based economy has reshaped firm value creation, not only in high-tech sectors but also in traditional manufacturing, through increased reliance on intangible investments. Intangible assets, characterized by distinctive economic properties, challenge neoclassical investment theories grounded in tangible capital. While existing literature focuses on their direct impacts on companies' performance, their role within the interaction of industrial structure and financial systems remains underexplored.

The analytical foundation for this study builds on the industry equilibrium model developed by Maksimovic and Zechner (1991), which characterizes how firms choose between projects of differing risk profiles in a competitive environment. In their framework, a *natural hedge* arises when a firm's production technology is close to the industry median. The mechanism works through competitive and endogenous price adjustment: when a majority of firms adopt the same technology, their cost shocks are absorbed into the industry output price. As a result, each firm's revenue becomes more correlated with its cost shock. As the share of adopters increases, this natural hedge strengthens, prices become more sensitive to the industry's common cost shock, and individual firms' profit variances decrease. This risk-sharing effect compresses the ex-post payoff distribution and reduces the firm's exposure to idiosyncratic shocks. MacKay and Phillips (2005) empirically validate this model, demonstrating that firms with capital–labor ratios closer to industry norms exhibit lower risk and higher leverage, particularly in competitive sectors.

This dissertation extends the theory and empirical framework to the intangible economy, where production technologies are increasingly unobservable, strategic, and financially opaque. It investigates whether intangible portfolios signal a firm's production technology and addresses the question: Do firms with industry-standard intangible portfolios exhibit lower distress risk? By examining how intangible position in industry affects firm's financial stability, this study contributes to the literature in three ways. First, the dissertation formally extends the Maksimovic and Zechner (1991) model by incorporating output-based uncertainty, investment timing frictions, and scalability properties, features that are characteristic of intangible capital. The model reveals that under these conditions, the natural hedge effect may be significantly weakened or even reversed. Secondly, using panel data and system GMM estimation, the study tests whether intangible portfolio alignment reduces cash flow volatility and supports higher leverage. It finds no evidence of a natural hedge, indicating a fundamental break from traditional theory. Thirdly, the findings are further interpreted with institutional frictions, such as the poor collateralizability and firm-specific nature of intangibles, as well as their strategic role as real options that incentivize deviation from industry norms.

The remaining sections are organized as follows: part (1) reviews the relevant literature across four crucial domains; part (2) presents the extended theoretical model of industry equilibrium under intangible investment; part (3) introduces the data selection, empirical design, and estimation strategy; part (4) presents the results of hypothesis testing, including subsample analyses and robustness checks; part (5) discusses the theoretical and policy implications, limitations, and avenues for future research.

2 Literature Review

While early studies focused on tangibles as the primary basis for valuation and collateral, traditional frameworks in accounting and finance have attributed limited attention to intangible capital. This literature review examines the four key perspectives: (1) the contribution of intangibles to firm value and performance, (2) the relationship between intangible intensity and capital structure, (3) industry equilibrium models linking innovation strategy to financial outcomes, and (4) corporate finance theories concerning firm financing structure.

2.1 Intangible assets, firm performance, and valuation

Early and recent studies consistently find that intangible assets are key drivers of firm value and performance. Many intangibles are expensed under conservative accounting, implying zero future benefit, yet research contradicts this notion. For example, Hirshleifer, Hsu, and Li (2013) show that a higher innovation efficiency predicts significantly higher future ROA, cash flows, and stock return. Such evidence confirms that internally developed intangible capital yields real economic benefits, even if not captured on balance sheets. In addition to multinational corporations listed in international databases, Seo and Kim (2020) show advertising-related intangibles improve profitability in Korean SMEs. To better quantify these effects, Peters and Taylor (2017) construct an improved Tobin's Q that capitalizes firms' R&D and a portion of SG&A as intangible capital, capturing knowledge and organizational capital beyond physical assets. Intangible capital thus appears to contribute strongly to productivity growth and market valuations, consistent with macro-level findings that intangibles now rival or exceed tangible assets in importance. With the proven critical role in driving firm value and growth, it is essential to exam how such assets interact with financial risk in operation.

2.2 Financial distress risk and capital structure

Classic corporate finance theory holds that high leverage increases distress probability, especially if earnings are volatile (Deakin, 1972; Beaver, 1968). Intangible-intensive firms often have more uncertain cash flows and own fewer pledgeable assets, which can limit their debt capacity. Myers (1977) and others note that growth options and R&D are hard to collateralize, leading to debt overhang and underinvestment problems. Empirical studies find intangible-heavy firms tend to use less debt, supporting the view that low collateral and high information asymmetry discourage borrowing. For instance, Clausen and Hirth (2016) document a negative correlation between intangible asset intensity and leverage. In line with this, Falato et al. (2022) link the rise of intangibles to a decline in U.S. firms' debt capacity, greater reliance on intangibles leads firms to borrow less and hold more cash for flexibility. Intangible assets also tend to lack liquidation value in bankruptcy, as they are often firm-specific and prone to obsolescence due to rapid technological advancement. This implies higher expected distress costs for intangible-rich companies, further incentivizing equity or internal financing. That said, recent evidence complicates the picture. Using detailed acquisition accounting data, Horsch et al. (2021) find that identifiable, enforceable and standardized intangible capital can support leverage capacity, especially when credibly recognized or collateralized. Similarly, Le et al. (2024) show that intangible assets improve SME financing access in Vietnam, particularly debt—challenging the view that all intangibles are equally credit-constrained. This contrasts with the traditional view that all intangible assets are equally constrained in credit markets. Lim et al. (2019) reports comparable findings, reinforcing the idea that intangible asset profiles materially influence capital structure choice and distress risk while standardized or well-defined intangible assets can ease financing frictions.

2.3 The Classical Industry equilibrium models

Theoretical models of industry equilibrium offer valuable insights into how market forces and agency costs interact to shape industry structure and firm risk. Maksimovic and Zechner's (1991) model introduces the idea that project risk is endogenously determined by the aggregate investment choices of all firms in the industry. If many firms adopt a given technology, product prices adjust to reflect that technology's cost, providing a "natural hedge" that stabilizes cash flows due to price-cost alignment. Many intangible investments, particularly in R&D, are not one-off projects but rather create valuable "real options", to make subsequent investments if market conditions prove favorable. The Real Options Theory (Myers, 1977) provides a crucial insight: the value of an option increases with the volatility of the underlying asset. This leads to a profound theoretical counterpoint to the natural hedge model, Real Options Theory predicts that innovative firms may have a strong incentive to pursue unique, non-standard, and therefore more volatile intangible investment strategies because this higher volatility maximizes the value of their portfolio of growth options. The potential for a breakthrough success (the high upside of the option) is more valuable than the stability offered by conforming to the industry norm.

While the agency cost framework developed by Vilasuso and Minkler (2001) argues that asset specificity, defined as the degree to which assets are tailored to particular uses or firms, increases monitoring costs and reduces the efficiency of debt as a financing instrument. Specific or opaque intangible assets exacerbate agency problems, such as moral hazard and underinvestment, particularly under high leverage. In contrast, more standardized or contractible intangible assets reduce these frictions by lowering information asymmetry and improving asset redeployability. As such, the degree of standardization in a firm's intangible portfolio may function as a structural determinant of both its capital structure and financial resilience.

Empirical work by MacKay and Phillips (2005) strongly supports these industry-equilibrium predictions. Studying manufacturing firms, they find that financial structure, technology choice, and risk are jointly determined within industries. In competitive industries, a firm's leverage depends on its position relative to industry peers, natural hedge, measured by the proximity of its capital–labor ratio to the industry median. Consistent with theory, MacKay and Phillips report a significant negative relationship between a firm's leverage and how far its technology departs from the industry median, along with a positive relationship between that deviation and the firm's cash-flow volatility. These patterns hold even in competitive industries, indicating they are not driven by monopoly power but by equilibrium forces. Overall, this body of work suggests that operating more closely to industry technical conditions could provide a hedge in terms of both industry dynamics and information transparency.

2.4 Intangibles and Corporate Finance

The corporate finance literature on signaling and agency costs link asset structure to financing constraints and distress. Signaling theories (Leland & Pyle, 1977; Ross, 1977) suggest that high-quality firms signal their worth through financing choices or collateral. Firms with more tangible and recognizable assets can credibly use collateralized debt to signal low risk while firms rich in novel intangibles lack such transparent signals. Their attempt to raise debt may be interpreted negatively by the market with higher cost of external finance as per the pecking-order theory of Myers and Majlu (1984). Moreover, collateral serves as a screening mechanism in credit markets (Boot & Thakor, 1994). Firms with tangible assets can pledge them, signaling low default risk, whereas those with unconventional intangibles cannot, potentially pooling with riskier types and facing adverse selection. Thus, asset standardization can be the key to smoother financing by lowering screening costs. However, the unique economic properties of intangible assets challenge these traditional, tangible-centric frameworks. As Crouzet et al. (2022) articulate, intangibles are best defined by their affirmative characteristics: non-rivalry in use and limited excludability. Non-rivalry means an intangible can be used simultaneously across multiple production lines, allowing for scalability. Limited excludability means it is difficult to prevent others from imitating the asset, making it hard to establish and enforce exclusive property rights. This second property is particularly critical for corporate finance, as it directly implies that intangibles are less pledgeable as collateral, undermining the traditional mechanisms for securing debt.

The literature provides strong evidence that intangible assets are central to firm performance and distress potential, but the impact depends on the nature of those intangibles and their alignment with industry norms. However, critical gap is also identified. One point of potential conflict is the performance-risk trade-off for innovative firms. While aligning with industry-standard intangibles seems to reduce risk, firms that deviate and innovate aggressively may achieve superior long-run performance, possibly offsetting their higher risk. For example, technology outliers may pioneer new markets and enjoy monopoly rents. Emerging evidence hints that intellectual intangibles can provide resilience against external shocks (Uddin et al., 2022). This suggests the relationship between intangibles and leverage is not static. Despite growing interest in these dynamics, there remains limited research on how the specificity of intangible portfolios, across firms and industries, affects firm-level financial stability. This study addresses that gap by measuring whether firms that are close to the median intangible asset composition can reduce firm-specific distress risk and support more robust capital structures.

3 Theoretical Model

This section discusses a competitive-industry model with two-stage production, in the spirit of Maksimovic and Zechner (1991) (referred as MZ afterwards), in which firms finance with debt, choose between a tangible technology (T) and an intangible-asset (IA) technology whose payoff is realized with a lag, and plan production before learning the state.

3.1 Output-realization Model

The model assumes there are n price-taking firms producing a homogeneous good. It holds the three-period setup from the MZ model, but with an additional period t_{2+1} which reflects investment lag.

At time t_0, the firm's initial owners choose a financial structure consisting of equity and pure discount debt with face value D, maturing at t_{2+1}. At time t_1, equityholders takes one of the mutually exclusive investment projects: a tangible technology (non-stochastic) or an intangible technology (stochastic). Different from the original model, uncertainty of intangible projects concerns technical feasibility and economic value (Freeman, 1982) which is output-realization related instead of cost-related. The choice of project determines the firm's production effectiveness (i.e., marginal costs) and quantity. The investment decision and the subsequent realization of production costs are private to the firm and not contractible; this precludes contingent contracting based on project choice or state realization.

At time t_2, the firm chooses a planned production quantity q^0. At time t_{2+1}, the technological state (i.e., success or failure) of the intangible investment is realized and all uncertainty is resolved. Output is then sold at a competitive price, and cash flows are distributed to claimholders according to contractual priority. The project's initial investment cost I_P is paid at t_1, and all payoffs occur at t_{2+1}.

For tractability, we make the standard assumptions of risk neutrality, and symmetric information after investment.

t_{2+1}: ***After Technology (State) Realization***

At time t_{2+1}, two equally probable technology state, denoted $\theta \in \{S, F\}$ for "Success" and "Failure," is realized. All cash flows are distributed to claimholders at this time. The realization of the state occurs after production has been planned, reflecting the investment lag that is intrinsic to intangible assets (Bar-Ilan & Strange, 1996). Thus, intangible project payoffs are only observed at t_{2+1}.

In state θ, industry output is determined by the number of firms adopting each technology. Let f denote the number of firms adopting the intangible (IA) technology, and $n - f$ the number adopting the tangible (T) technology. The total industry output in state θ is

$$Q^{\theta} = f q_{IA}^{\theta} + (n - f) q_T, \tag{1}$$

where, for intangible adopters,

$$q_{IA}^{\theta} = \begin{cases} q_{ind} + y, & \theta = S \\ q_{ind}, & \theta = F \end{cases} \tag{2}$$

and for tangible adopters,

$$q_T = q_{ind} + \epsilon \tag{3}$$

with $0 < \epsilon < y$. q_{ind} is the prior output for each firm before investment choice in t_1 which is common across the industry. Output is sold in a competitive market, so the equilibrium price in each state is

$$p^{\theta} = a - bQ^{\theta}. \tag{4}$$

Since $Q^S > Q^F$, it follows immediately that $p^S < p^F$.

t_2: *Production Decision Before Learning* θ

At time t_2, each firm chooses its planned production quantity with expectation depending on the state. For intangible adopters, the firm receives an additive, zero-cost output boost $y > 0$ above the industry-standard production quantity in the success state. For tangible adopters, the planned output is $q_T = q_{ind} + \epsilon$ with $0 < \epsilon < y$. Therefore, the realized output ordering is $q_{IA}^F < q_T < q_{IA}^S$.

Equityholders from firms choose project T solve the maximization problem:

$$\max_{q} \ \mathbb{E}[p^{\theta}]q_T - C(q_T), \tag{5}$$

where $\mathbb{E}[p^{\theta}] = a - b\mathbb{E}[Q^{\theta}]$ and $C(q_T)$ denotes the total production cost of type T. Similarly, firm chooses project IA solve

$$\max_{q} \ \mathbb{E}[p^{\theta} q_{IA}^{\theta} - C(q_{IA}^{\theta}, \theta)], \tag{6}$$

with cost $C(q_{IA}^{\theta}, \theta)$ dependent on the state and project. Firms are assumed to be price takers and consider the expected output of all firms in their production planning.

t_1: *Equityholders' Investment Decision*

At time t_1, equityholders choose an investment project, $P \in \{\text{IA}, T\}$, paying a project-specific investment outlay I_P. Consistent with the economics of intangibles, we assume

$I_{IA} > I_T$ since intangible assets require a larger upfront investment and longer deployment. The marginal cost curves for each project are

$$MC(IA) = \begin{cases} k + \gamma_{IA} q, & \theta = S \\ k + \gamma_{ind} q, & \theta = F \end{cases} \tag{7}$$

and

$$MC(T) = k + \gamma_T q, \tag{8}$$

with $\gamma_{IA} < \gamma_T < \gamma_{ind}$.

The model incorporates two sources of state-dependent uncertainty: output realization (Equation (1)) and marginal production cost (Equation (7)). The stochastic marginal cost is designed to reflect the enhanced scalability inherent in successful intangible assets. A successful innovation not only increases output but also makes the production of that output more efficient. This feature amplifies the payoff in the 'Success' state, reinforcing the high-variance profile of the intangible investment.

For a given production plan, the firm's total profit is the sum of profits earned in periods t_2 and t_{2+1}, denoted as π_P^θ in state θ. Equityholders at t_1 select the project that maximizes $E(D, P)$:

$$E(D, T) = \lambda \left[\frac{1}{2} \max\{\pi_T^S, 0\} + \frac{1}{2} \max\{\pi_T^F, 0\} \right] - I_T, \tag{9}$$

$$E(D, IA) = \lambda \left[\frac{1}{2} \max\{\pi_{IA}^S, 0\} + \frac{1}{2} \max\{\pi_{IA}^F, 0\} \right] - I_{IA}, \tag{10}$$

where λ is a discount factor for delayed payoff realization. For simplicity, $\lambda = 1$.

t_0: *Capital Structure Decision*

At time t_0, the firm owners select the face value D of pure discount debt so as to maximize firm value:

$$\max_D V(P(D)) = E(D, P(D)) + B(D, P(D)),$$

where $B(D, P(D))$ is the value of debt for a given project choice and debt level.

3.2 Financial Structure, Risk-Shifting, and Distress

3.2.1 The Industry Equilibrium Distribution

In industry equilibrium, the number of firms choosing each project adjusts until expected firm values are equalized. For the intangible (IA) and tangible (T) technologies to be indifferent, we require:

$$\mathbb{E}[V(IA)] = \mathbb{E}[V(T)] \tag{11}$$

Proposition 1. *If the investment difference is sufficiently small, then f^* firms choose the intangible project and $(n - f^*)$ firms choose the tangible project, where:*

$$f^* = \frac{(y^2 - 2\gamma I^*)(bn + \gamma)}{2by^2}, \quad \textit{with } I^* = I_{IA} - I_T > 0$$

The equilibrium condition ensures that despite higher upfront investment costs for intangibles, the expected value is equalized through differential cash flow distributions.

3.2.2 The Riskiness of Project Cash Flows

The key insight from extending the MZ model to intangibles is that cash flow riskiness is endogenously determined by adoption patterns, but now through output-based rather than cost-based uncertainty.

Lemma 1. *In equilibrium, the following profit ordering holds:*

$$\pi_{IA}^S > \pi_T^F > \pi_T^S > \pi_{IA}^F$$

Proposition 2. *The net cash flows of the intangible project exhibit greater dispersion than the tangible project. Specifically, the intangible project's cash flows are a mean-preserving spread of the tangible project's cash flows.*

Unlike MZ's cost-based natural hedge, the *natural hedge* mechanism operates through competitive price absorption of output shocks. When more firms adopt intangible technology, aggregate output becomes more sensitive to the realization of technological state. Price movements $p^S < p^F$ partially offset individual firms' output variations. This creates a natural hedge that reduces cash flow volatility for intangible adopters.

Hence, a primary hypothesis can be formed as follows:

H 1. *Firms with intangible asset portfolios closer to the industry median exhibit lower cash flow volatility compared to firms at the technological fringe, controlling for other determinants of risk.*

Furthermore, the model establishes a clear division between the two distinct projects. While the model itself does not explicitly include a role for collateral, hypothesis 2 tests a key economic reason for the behavioral and financial distinctions between T and IA assets. It suggests that the natural hedge's ability to stabilize a firm and support its financial structure is critically dependent on the collateralizability of its assets. Tangible assets, being easily pledgeable, allow the hedge to function effectively. Intangible assets, lacking this collateral capacity, cannot leverage the stabilizing effect of the hedge in financial markets.

H 2. *The risk-reducing effect of asset standardization (i.e., the natural hedge) is significantly stronger for tangible capital and identifiable intangible capital than for other kinds of intangible capital.*

3.2.3 The Asset Substitution Channel

Proposition 3. *Define* $D^{\max} = \pi_{IA}^F - 2I_{IA}$*. Then equityholders with riskless debt* ($D \leq \pi_T^F$) *are indifferent between projects. Equityholders with risky debt* ($\pi_T^F < D \leq D^{\max}$) *strictly prefer the intangible project. For* $D > D^{\max}$*, equityholders do not invest.*

The intangible project is a mean-preserving spread of the tangible project as established in Lemma 1 where the intangible project has both the highest possible payoff (in the 'Success' state) and the lowest possible payoff (in the 'Failure' state). When debt is risky (i.e., $D > \pi_T^F$), equityholders' claim behaves like a call option on the firm's assets. Their downside is limited—the most they can lose is their investment, as bondholders bear the losses in bankruptcy. However, they retain all the upside potential. This creates a classic asset substitution or risk-shifting incentive (Jensen & Meckling, 1976). Equity holders are incentivized to choose the project with the highest variance because they fully capture the gains from the extremely high payoff in the success state (π_{IA}^S) and are shielded from the full impact of the extremely low payoff in the failure state (π_{IA}^F).

In contrast, the MZ model's result is a consequence of their specific setup where the "natural hedge" makes the risky project less volatile for adopters as the adoption rate increases. While the risky project (S) has a higher payoff in the good state (L, low cost), the natural hedge mechanism compresses this payoff distribution. This output-based uncertainty structure creates a more asymmetric payoff than the cost-based uncertainty in the original framework.

Therefore, if higher leverage leads firms to choose riskier projects (i.e., intangible investments), then it should be empirically observed that an increase in leverage is followed by an increase in the firm's overall operating risk, especially for intangible-intensive firms.

H 3. *An increase in a firm's leverage is associated with a subsequent increase in its operating or market risk, and this positive relationship is significantly stronger for firms with a higher intensity of intangible investment (particularly R&D).*

4 Data and Methodology

This study uses firm-level data from the COMPUSTAT North America database, accessed through Wharton Research Data Services (WRDS). The sample covers both active and inactive firms incorporated in the United States and Canada, with the financial service industry excluded, for the period from 2000 to 2024 [1]. Financial accounting and operational variables are sourced from the same database to maintain consistency across measures. Following empirical strategies from literature on industry equilibrium and firm financial structure, the dataset supports analysis of both firm-specific dynamics and industry-level interactions (Maksimovic & Zechner, 1991; MacKay & Phillips, 2005). This approach allows for analysis of how proximity to the industry's technological and capital composition affects leverage and risk outcomes, in line with the "CHS framework" that incorporates intangible capital into measures of investment and productivity (Corrado, Hulten, & Sichel, 2005).

4.1 Sample selection

The sample construction follows a series of data screening to ensure reliability and comparability across firms. Observations with non-positive total assets or missing values for intangible assets and research and development expenditures are excluded to reduce distortions in variables central to the analysis. Consistent with prior studies, firms in the

[1] This timeframe ensures comprehensive coverage and enhances the consistency of reporting for intangible-related variables, such as intangible assets (item *intan*) and research and development expenditures (item *xrd*). These variables are of particular significance in the North American context, where investment intensity in intangible capital is recognized as the highest globally, as evidenced by the World Intellectual Property Organization and Luiss Business School's (2025) World Intangible Investment Highlights.

financial sector are left out. As the dynamic panel regression estimation requires a two-period lag structure, only firms with a minimum of three consecutive annual observations are retained. After applying these filters, the resulting dataset forms an unbalanced panel comprising 4,681 firms and 36,110 firm-year observations. To allow comparison with the tangible technology proxy of McKay & Phillips (2005), the same Herfindahl–Hirschman index (HHI) threshold is used to classify industries as either "competitive" or "concentrated"[2]. The "competitive" group includes 1,754 firms from 24 industries (11,647 firm-year observations), while the "concentrated" group consists of 2,927 firms from 61 industries (24,463 firm-year observations). Because the model of Maksimovic & Zechner (1991) is grounded in a competitive market setting, the hypotheses are tested using the "competitive" subsample, with results for the "concentrated" subsample and full dataset reported as complements. This sampling design captures the heterogeneity of firms across industries while ensuring adequate temporal depth for econometric identification.

4.2 Proxies and key variables

The purpose of this study is to empirically test the predictions of the theoretical model developed in Section 3. The model extends Maksimovic and Zechner's (1991) industry-equilibrium framework by introducing intangible investments with delayed payoff realization. It shows that when firms adopt intangible portfolios that are close to the industry median, competitive price adjustments absorb common shocks, creating a natural hedge that compresses the variance of cash flows.

4.2.1 Financial Distress Risk

Financial distress risk is defined as the probability that a firm will be unable to meet its financial obligations due to rising leverage, volatile cash flows, or deteriorating liquidity. Classic empirical work demonstrates that leverage ratios and cash flow volatility remain statistically significant predictors of corporate bankruptcy (Beaver, 1968; Deakin, 1972). Following this literature, two indicators are adopted: the leverage ratio is measured by total debt divided by total assets, which reflects a firm's exposure to debt-related obligations; cash flow volatility is captured by the standard deviation of operating cash flow divided by total assets, which measures stability in a firm's internal financing capacity. Beyond these static measures, the two-period model by Hirth and Viswanatha (2011) demonstrates the dynamic interaction between financing frictions and investment under

[2]The U.S. Department of Justice defines an industry as "competitive" with an HHI below 1800 and "concentrated" with an HHI above 1800.

uncertainty. They show that firms facing high external financing costs today are particularly sensitive to cash flow risk, as elevated volatility increases the likelihood of future underinvestment. This insight highlights the role of cash flow volatility not just as a distress symptom but as a forward-looking constraint on firm behavior.

4.2.2 Intangible Portfolio

The second dimension of analysis is the firm's intangible portfolio, based on the framework by Corrado, Hulten, and Sichel (2005) and later refinements in intangible capital measurement. Traditional accounting practices like GAAP (Generally Accepted Accounting Principles) and IFRS (International Financial Reporting Standards)[3] often expenses R&D, training, and brand development, which understates a firm's capital base and overstates current costs. In contrast, the CHS accounting approach capitalizes intangible investments, explicitly highlights their contribution to productivity and growth, and embeds intangible investment in a utility-maximizing neoclassical framework.

Each category contributes to the firm's technological capacity, and the composition of investment determines the company's intangible portfolio. Building on this established framework, I construct three proxies to capture the key features of a firm's intangible portfolio in a way that allows for consistent comparison across industries. First, I use the R&D intensity, measured by R&D expenses divided by total revenue (denoted as $Z_{R\&D}$), as a proxy of the knowledge capital a firm owns. The New Growth Theory suggests intangible investment represents R&D and knowledge accumulation efforts that augment the firm's stock of technological capital and support long-term growth (Corrado et al., 2022). Then, I use the standard intangible asset ratio, measured by the sum of all intangible assets divided by total assets (denoted as Z_{IA}), as a proxy for intangible investment effort. The last variable, identifiable intangible ratio (denoted as Z_{ID}), is less trivial. For an intangible asset to be identifiable, it must either be separable from the entity or it must derive from contractual and other legal rights. Peters & Taylor (2017) consider a large part of SG&A represents an investment in organizational capital, which is also recognized as non-identifiable intangible (Lim et al., 2019). Hence, subtracting the ratio would give us the identifiable intangible, which is often omitted or not explicitly reported in the dataset. As Compustat reports the sum of R&D and SG&A under the variable labelled "Selling, General and Administrative Expense" (item *xsga*), I follow the

[3]Under GAAP, research and development (R&D) costs are recognized as expenses when incurred, and intangible assets are carried at historical cost, with revaluations to fair value explicitly prohibited. IFRS (IAS38) allows the capitalization of development costs but with specific criteria, such as technical feasibility and probable future economic benefits. Source: RSM US LLP. (2022). U.S. GAAP versus IFRS: Intangible assets other than goodwill. RSM. https://rsmus.com/content/dam/rsm/insights/financial-reporting/us-gaap-vs-ifrs-comparisons/us$_gaap_ifrs_intagible_assets_other_than_goodwill.pdf$

Table 1: *Intangible classification table under CHS framework*

Category	**Classification**	**Accounting under NIPAs**
Economic competencies	Investment on strategic planning, redesigning or reconfiguring existing products, retain or gain market share, and brand names: (a) Brand Equity: advertising (b) Firm-Specific Resources: human and structural resources (e.g., training programs)	No items recognized as assets of firm
Innovative property	Investment on R&D in two types: (a) Scientific R&D: innovative activity built on a scientific base of knowledge (e.g., Patent, copyrights) (b) Non-scientific R&D: resources devoted by businesses to innovation and new product/process R&D (e.g., product design, movie production)	Most spending for new product discovery and development is expensed
Computerized information	Business investment in computer software.	Major component is capitalized

same method as Peters & Taylor (2017) to subtract *xrd* from *xsga* to isolate the SG&A expense.

Analogous to the use of the capital-to-labor ratio in MacKay & Phillips (2005), I use Principal Component Analysis (PCA) to construct a single latent variable (i.e., Intangible portfolio) from the three correlated observed variables by extracting the linear combination that captures the most variation in the data.

For firm i at time t,

$$IP_{it} = w_1 Z_{R\&D,it} + w_2 Z_{IA,it} + w_3 Z_{ID,it}$$

where the weights (w_1, w_2, w_3) are endogenously derived from PCA. The choice of approach is justified by application in a similar research setting, using PCA to combine multiple intangible indicators into a composite measure of knowledge capital and reflect the complex interdependencies of intangible investment (Nonnis et al., 2022). Likewise, Román-Aso et al. (2021) construct a firm-level index of financial conditions using PCA, showing that the technique effectively condenses correlated financial variables into a single underlying dimension that is comparable across firms and industries. These studies provide empirical examples for applying PCA in contexts where multiple financial proxies must be aggregated into a tractable measure for analysis.

Following the industry-equilibrium framework of MacKay & Phillips (2005), the proxy for Natural Hedge has to reflect a firm's production technology and be comparable across industries. The finding that firm productivity is positively influenced by both internal knowledge capital and regionally available intangible assets (Marrocu et al., 2012) provides a basis for reinterpreting a firm's intangible asset composition as its technological identity. Therefore, a firm with an intangible portfolio that closely tracks the industry-standard patterns is considered as operating at the "technological core" of its industry. Formally, the measure compares a firm's intangible portfolio to the median portfolio of its industry peers in year t.

For each firm f in industry i in year t:

$$\text{Natural Hedge}_{f,i,t} = \frac{|\text{IP}_{f,i,t} - \text{median}_{i,j,-t}(\text{IP})|}{\text{range}\{|\text{IP}_{f,i,t} - \text{median}_{i,j,-t}(\text{IP})|\forall f \in i, t\}} \in [0, 1]$$

A natural hedge with higher values indicating proximity to the industry's technological core.

4.3 Empirical model specification

To empirically examine the joint dynamics between financial structure, firm-level risk, and technological positioning, the analysis adopts a simultaneous equation framework estimated using the Generalized Method of Moments (GMM). This specification reflects the economic structure implied by competitive industry equilibrium models (Maksimovic & Zechner, 1991), where a firm's financing decisions influence its technology investment, and vice versa. The empirical strategy closely follows MacKay & Phillips (2005) with simplified control variables. The core equations model changes in leverage, cash flow volatility, and intangible portfolio position as interdependent outcomes driven by firm behaviour and strategic positioning. The simultaneous system is written as follows:

$$\begin{aligned}
\Delta\text{Leverage}_t &= f(\Delta\text{IP}_t, \Delta\text{CFV}_t, \Delta\text{NH}_t, \Delta\text{Controls}_t) + \tilde{\varepsilon}_t \\
\Delta\text{CFV}_t &= g(\Delta\text{IP}_t, \Delta\text{Leverage}_t, \Delta\text{NH}_t, \Delta\text{Controls}_t) + \tilde{\upsilon}_t \\
\Delta\text{IP}_t &= g(\Delta\text{Leverage}_t, \Delta\text{CFV}_t, \Delta\text{NH}_t, \Delta\text{Controls}_t) + \tilde{\eta}_t
\end{aligned}$$

where Δ is the lag operator for one period, , , and are random error terms, and the right-hand side variables (financial leverage, cash-flow volatility, natural hedge proxy, profitability, size, diversification, Tobin's q, and collateral ratio) are instrumented with their twice-lagged values. An important addition is collateral capacity, proxied by the ratio of the tangible assets (item *ppegt*) to total assets. This control accounts for variation in firms' ability to pledge assets in financial markets, which directly affects leverage and financial distress risk (Holmstrom & Tirole, 1997). By controlling for collateral capacity, the model isolates the effect of a firm's portfolio composition (relative to the industry norm) from its balance sheet-based borrowing ability, ensuring that observed differences in financial risk are not merely a function of pledgeability constraints. This distinction identifies whether it is the technological position of a firm within its industry, rather than its general asset quality, that drives variation in financial distress outcomes.

The choice of GMM is justified on both economic and econometric grounds. Economically, the system reflects a recursive feedback loop where firm outcomes are jointly determined, meaning single-equation estimation would yield biased and inconsistent coefficients. Statistically, GMM addresses endogeneity bias by instrumenting for potentially endogenous regressors using their own lagged values, as shown in Whited (1992) and Arellano & Bond (1991). Moreover, first-differencing the panel data removes firm-level fixed effects, such as unobserved management quality or persistent business models, isolating the effects of within-firm changes rather than level differences.

5 Results

The empirical results test the hypotheses derived from the theoretical model. The model predicts that while a ”natural hedge” from industry alignment may exist, it is potentially overshadowed by risk-shifting incentives tied to leverage and the unique, non-collateralizable nature of intangible assets. Building on these predictions, the results are organized to first describe the data patterns, then report baseline GMM estimates and OLS benchmark model of leverage, cash-flow volatility, and intangible positioning, before examining the role of collateral capacity and conducting robustness checks.

5.1 Descriptive Statistics

Table 2: Summary Statistics by Industry Type

	Mean	Median	SD	Range	Firm-year obs
Competitive					
Leverage	0.317	0.231	0.984	55.428	11647
Cash flow volatility	0.091	0.041	0.231	3.539	11647
Intangible Portfolio	-0.007	-0.156	0.909	22.844	11647
Natural Hedge	0.890	0.946	0.151	1.000	11647
Profitability	-0.024	0.040	0.478	25.000	11647
Size: log(AT)	6.679	6.723	2.397	15.043	11647
Concentrated					
Leverage	0.274	0.196	0.709	56.109	24464
Cash flow volatility	0.088	0.045	0.198	3.705	24464
Intangible Portfolio	0.007	-0.087	0.920	18.862	24464
Natural Hedge	0.757	0.857	0.266	1.000	24464
Profitability	-0.027	0.063	0.815	90.575	24464
Size: log(AT)	6.371	6.449	2.507	19.399	24464
Total					
Leverage	0.287	0.205	0.808	56.109	36111
Cash flow volatility	0.089	0.044	0.209	3.705	36111
Intangible Portfolio	0.002	-0.116	0.917	26.035	36111
Natural Hedge	0.799	0.899	0.243	1.000	36111
Profitability	-0.026	0.055	0.724	92.075	36111
Size: log(AT)	6.471	6.541	2.476	19.399	36111
Observations	36111				

Table 2 reports summary statistics for main variables segmented by industry concentration. The sample reveals wide dispersion in leverage ratios, cash flow volatility, and intangible asset positioning. In the full sample of 36,111 firm-year observations, the average book leverage ratio is 0.287, with substantial variability (SD = 0.808). The intangible portfolio (IP) measure has a sample mean close to zero (0.002) and a standard deviation of 0.917. The natural hedge (NH) index, which captures proximity to the industry's intangible norm, averages 0.799, with a median of 0.899. These results suggest that most firms cluster around their industry's technological core, but with meaningful variation in alignment. Firms in competitive industries report higher leverage on average (mean 0.317 ¿ 0.274) and greater cash flow volatility (mean 0.091 ¿ 0.088) than those in concentrated industries. Similarly, the average NH values are higher in competitive sectors, implying that firms in more fragmented environments tend to maintain closer technological proximity to industry norms, potentially due to heightened peer pressures or lower entry barriers. This is consistent with the theoretical predictions of MacKay Phillips (2005), where firm heterogeneity within competitive industries supports the role of intra-industry equilibrium forces in shaping financial structure.

5.2 Baseline GMM Estimates OLS Comparison

Table 3 presents the primary findings from both Ordinary Least Squares (OLS) and System GMM estimations from the three core equations: changes in book leverage (Column 1), cash flow volatility (Column 2), and intangible portfolio positioning (Column 3).

5.2.1 Determinants of Leverage

In the GMM model, the IP variable has a positive but insignificant effect ($\beta = 0.059$) on leverage. The empirical evidence does not support the prediction that technological positioning near the industry median provides a significant "natural hedge" that reduces leverage. Hence, H1 is rejected. This "failure" of the natural hedge for intangible assets is a key finding. A plausible explanation, consistent with the model's broader framework, is that the inherent risk and lack of pledgeability of intangible assets create financing frictions and incentives that overwhelm any stabilizing effects from competitive price adjustments. Cash flow volatility greatly affects the degree of leverage, with a coefficient of 5.513.

Table 3: OLS and System GMM Results for Competitive Industries

	Ordinary Least Squares			**System GMM**		
	Leverage	Cash flow volatility	IP	Leverage	Cash flow volatility	IP
Dependent variables						
Intangible portfolio	0.013	-0.007***		0.059	-0.042	
	(0.011)	(0.002)		(0.211)	(0.039)	
Cash flow volatility	-0.344***		0.051	5.513*		1.176
	(0.062)		(0.072)	(2.917)		(0.972)
Leverage		-0.011***	0.034**		-0.011	0.057
		(0.002)	(0.015)		(0.009)	(0.118)
Instrument variables						
Natural Hedge	0.117**	-0.001	0.028	0.013	-0.100	0.524
	(0.051)	(0.008)	(0.059)	(0.270)	(0.077)	(0.326)
Profitability	0.108***	-0.011***	-0.020	0.285**	-0.005	0.070
	(0.013)	(0.002)	(0.016)	(0.124)	(0.006)	(0.090)
Size: log(at)	-0.054**	-0.011***	0.059**	-0.032	0.003	-0.055
	(0.022)	(0.004)	(0.025)	(0.105)	(0.016)	(0.041)
Tobin's q	-0.010***	-0.000	0.005***	-0.017	-0.001**	0.004
	(0.001)	(0.000)	(0.001)	(0.041)	(0.000)	(0.004)
Collateral ratio	0.015	-0.018**	-0.196***	-0.078	-0.034**	-0.116
	(0.053)	(0.009)	(0.061)	(0.237)	(0.014)	(0.156)
HHI	-0.222	-0.016	-0.032	0.284	0.038	-0.355
	(0.356)	(0.059)	(0.414)	(0.407)	(0.050)	(0.417)
Observations	7212	7212	7212	7212	7212	7212
Adjusted R^2/Wald χ^2	0.030	0.008	0.005	4.260	4.320	2.170
Hansen J-statistic (χ^2, df = 6)		n/a		5.170	6.700	7.380
AR(2) p-value		n/a		0.270	0.110	0.046

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.2 Determinants of Cash Flow Volatility

The GMM results show that neither the intangible portfolio, leverage, nor the Natural Hedge variable has a statistically significant effect on cash flow volatility. The coefficient for leverage as a determinant of cash flow is small, negative, and statistically insignificant. The results reject H3, the asset substitution hypothesis. Contrary to the model's prediction, firms with higher leverage do not exhibit a subsequent, statistically significant increase in cash flow volatility. This suggests that the classic risk-shifting channel, while theoretically powerful, may be constrained by other factors in practice, such as debt covenants, monitoring by lenders, or managerial risk aversion. The incentive to take on riskier (intangible) projects may not translate directly into higher observable cash flow volatility.

5.2.3 Determinants of Intangible Portfolio

The decision to change a firm's intangible portfolio is not significantly driven by past leverage or cash flow volatility in the GMM model. This provides no evidence of reverse causality from capital structure to intangible alignment.

5.2.4 Robustness Check

To ensure the robustness of the primary findings, Table 3 provides a comparison between the System GMM results and those from a standard Ordinary Least Squares (OLS) model. The OLS estimates diverge considerably from the GMM results, highlighting the presence of significant endogeneity bias that the OLS model fails to address. For example, cash flow volatility shows a strong, statistically significant negative relationship with leverage in the OLS specification, whereas this effect becomes positive and insignificant in the GMM model, which controls for reverse causality. This pattern of variables losing significance is repeated across the equations, validating the choice of System GMM as the more appropriate and reliable estimation strategy for analyzing the interdependent relationships between leverage, risk, and intangible investment.

Table 4: Subsample and Interaction GMM Results: Leverage Equation

Dependent var.	(1) Low leverage	(2) High leverage	(3) Leverage
Key independent var.			
Intangible Portfolio	-0.003	-0.230	0.021
	(0.016)	(0.522)	(0.123)
Cash flow volatility	-0.128	5.333	0.890
	(0.221)	(4.673)	(3.390)
Natural Hedge	-0.007	-0.638	-0.122
	(0.038)	(0.770)	(0.150)
Instrument var.			
profitability	0.016	0.209	-0.014
	(0.020)	(0.299)	(0.281)
Size: log(at)	0.001	-0.238	-0.176
	(0.008)	(0.370)	(0.270)
Tobin's q	-0.002***	-0.004	0.001
	(0.000)	(0.012)	(0.009)
Collateral ratio	-0.003	-0.247	-0.914
	(0.019)	(0.657)	(1.303)
HHI	-0.082	0.471	-0.024
	(0.203)	(0.582)	(0.082)
Interaction term.			
ip_x_collateral	-0.030	-6.948	-0.202
	(0.082)	(6.157)	(1.178)
Observations	4619	11824	36560

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Role of Collateral Capacity in Mediating Leverage–Risk Link

Table 4 tests a direct implication of this hypothesis: whether tangible collateral can help intangible-aligned firms secure more debt, thereby translating the "hedge" into financial stability, following theoretical arguments that tangible or identifiable intangible assets with pledgeability can help overcome the financing frictions typically faced by intangible-intensive firms (Morris, 1987). To formally assess this, the leverage equation is re-estimated across subsamples split by debit capacity, proxied by leverage, as well as with a direct interaction term between the intangible portfolio index and collateral ratio. By setting the threshold of leverage ¿ 0, firms are divided into two groups: low leverage and high leverage. Regression results are reported in column (1) and (2), respectively. Column (3) is the full sample test result. This analysis is crucial for testing the hypothesis that the financial benefits of asset standardization depend on the pledgeability of those assets. The key variable of interest is the interaction term, *ip_x_collateral*, defined as the product of lagged intangible portfolio change and lagged collateral ratio. Across all specifications, including subsamples split by leverage levels and the full sample interaction model, the interaction term is statistically insignificant. In the full sample (Column 3), the coefficient on *ip_x_collateral* is -0.202 (SE = 1.178), providing no evidence that a higher collateral ratio enhances the ability of intangible-aligned firms to take on more debt. The direct effects of the intangible portfolio and the collateral ratio on leverage are also insignificant in this model. While the interaction term does not achieve statistical significance, the negative point estimate contradicts the hypothesis that high collateral mitigates the leverage constraints associated with intangible intensity. One interpretation is that collateral capacity and intangible capital may be complements only under certain structural conditions, such as when intangibles are partially capitalized or secured (e.g., through patents or trademarks). Alternatively, measurement error in collateral estimation may underestimate the true interaction effect. The consistency among the direction of effects and theoretical predictions suggests scope for further investigation using refined measures of collateral quality or enforceability.

6 Conclusion

This study investigates how a firm's intangible asset portfolio, relative to its industry peers, influences its financial structure and distress risk. Grounded in the theoretical insights of industry equilibrium models, particularly Maksimovic and Zechner (1991), and building on the empirical strategies of MacKay and Phillips (2005), this dissertation examines whether the logic of industry-driven risk hedging extends to the modern intangible economy.

The empirical evidence largely fails to support the key hypotheses derived from this theoretical framework. First, the results do not show that technological proximity to the industry median—the core of the "natural hedge" mechanism—significantly reduces cash flow volatility. This suggests that for intangible assets, technological conformity is insufficient to provide a meaningful hedge against risk. Second, the analysis finds no support for the classic asset substitution channel, as higher leverage is not associated with a subsequent increase in cash flow volatility. Finally, interaction models reveal that tangible collateral does not mitigate the financing frictions faced by intangible-intensive firms; its presence fails to strengthen their leverage capacity. Collectively, these findings indicate that traditional tangible collateral remains a dominant determinant of debt capacity and that standardized intangible portfolios, while conceptually promising, do not currently possess equivalent economic signaling power in financial markets.

The dissertation also contributes theoretically by extending the notion of a natural hedge from a cost-based framework to one centered on revenue-based uncertainty, aligning with the economic nature of intangible-intensive production. The model incorporates investment lags and output dispersion, both central features of intangible capital, to better capture their implications for financial decision-making.

Overall, this study advances the literature by empirically validating parts of the industry equilibrium logic in the context of intangible capital. It bridges macro-level industry dynamics with micro-level financial behavior, offering insights into how firms can strategically position their intangible investments to potentially mitigate distress risk. At the same time, it highlights that without adequate mechanisms for standardization, enforceability, or capital market recognition, intangible alignment alone is insufficient to overcome leverage constraints. Future research may explore how policy changes in accounting standards, credit rating treatment, or asset securitization could elevate the financing potential of intangible capital and deepen our understanding of financial resilience in the knowledge economy.

References

[1] Bar-Ilan, A., & Strange, W. C. (1996). Investment lags. *The American Economic Review, 86*(3), 610–622. http://www.jstor.org/stable/2118214

[2] Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*, 71–111. https://doi.org/10.2307/2490171

[3] Bolton, P., Wang, N., & Yang, J. (2020). Leverage dynamics and financial flexibility. *National Bureau of Economic Research.*

[4] Boot, A. W., & Thakor, A. V. (1994). Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review*, 899–920.

[5] Clausen, S., & Hirth, S. (2016). Measuring the value of intangibles. *Journal of Corporate Finance, 40*, 110–127.

[6] Corrado, C., Hulten, C., & Sichel, D. (2009). Intangible capital and U.S. economic growth. *Review of Income and Wealth, 55*(3), 661–685. https://doi.org/10.1111/j.1475-4991.2009.00343.x

[7] Crouzet, N., Eberly, J. C., Eisfeldt, A. L., & Papanikolaou, D. (2022). The economics of intangible capital. *Journal of Economic Perspectives, 36*(3), 29–52.

[8] Deakin, E. B. (1972). A discriminant analysis of predictors of business failure. *Journal of Accounting Research, 10*(1), 167–179. https://doi.org/10.2307/2490225

[9] Falato, A., Kadyrzhanova, D., Sim, J., & Steri, R. (2022). Rising intangible capital, shrinking debt capacity, and the US corporate savings glut. *The Journal of Finance, 77*(5), 2799–2852.

[10] Freeman, C., & Soete, L. (1997). *The Economics of Industrial Innovation.* Routledge. https://doi.org/10.4324/9780203064474

[11] Hirshleifer, D., Hsu, P.-H., & Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics, 107*(3), 632–654. https://doi.org/10.1016/j.jfineco.2012.09.011

[12] Holmstrom, B., & Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics, 112*(3), 663–691.

[13] Horsch, P., Longoni, P., & Oesch, D. (2021). Intangible capital and leverage. *Journal of Financial and Quantitative Analysis, 56*(2), 475–498.

[14] Hirth, S., & Viswanatha, M. (2011). Financing constraints, cash-flow risk, and corporate investment. *Journal of Corporate Finance, 17*(5), 1496–1509.

[15] Le, C., Nguyen, B., & Vo, V. (2024). Do intangible assets help SMEs in underdeveloped markets gain access to external finance?—The case of Vietnam. *Small Business Economics, 62*(2), 833–855.

[16] Leland, H. E., & Pyle, D. H. (1977). Informational asymmetries, financial structure, and financial intermediation. *The Journal of Finance, 32*(2), 371–387.

[17] Lim, S. C., Macias, A. J., & Moeller, T. (2020). Intangible assets and capital structure. *Journal of Banking & Finance, 118*, 105873.

[18] MacKay, P., & Phillips, G. M. (2005). How does industry affect firm financial structure? *Review of Financial Studies, 18*(4), 1433–1466. https://doi.org/10.1093/rfs/hhi032

[19] Maksimovic, V., & Zechner, J. (1991). Debt, agency costs, and industry equilibrium. *The Journal of Finance, 46*(5), 1619–1643.

[20] Marrocu, E., Paci, R., & Pontis, M. (2012). Intangible capital and firms' productivity. *Industrial and Corporate Change, 21*(2), 377–402.

[21] Meckling, W. H., & Jensen, M. C. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305–360.

[22] Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics, 5*(2), 147–175.

[23] Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics, 13*(2), 187–221.

[24] Nonnis, A., Bounfour, A., & Kim, K. (2023). Knowledge spillovers and intangible complementarities: Empirical case of European countries. *Research Policy, 52*(1), 104611.

[25] Ogden, J. P., & Wu, S. (2013). Reassessing the effect of growth options on leverage. *Journal of Corporate Finance, 23*, 182–195.

[26] Román-Aso, J. A., Coca Villalba, F., Mastral Franks, V., & Bosch Frigola, I. (2021). Using principal component analysis to create an index of financial conditions in Spain: Differences by firm size and industry.

[27] Ross, S. A. (1977). The determination of financial structure: The incentive-signalling approach. *The Bell Journal of Economics, 8*(1), 23–40.

[28] Seo, H. S., & Kim, Y. (2020). Intangible assets investment and firms' performance: Evidence from small and medium-sized enterprises in Korea. *Journal of Business Economics and Management, 21*(2), 421–445.

[29] Uddin, M. R., Hasan, M. M., & Abadi, N. (2022). Do intangible assets provide corporate resilience? New evidence from infectious disease pandemics. *Economic Modelling, 110*, 105806.

[30] Vilasuso, J., & Minkler, A. (2001). Agency costs, asset specificity, and the capital structure of the firm. *Journal of Economic Behavior & Organization, 44*(1), 55–69.

[31] Williams, J. (1995). Financial and industrial structure with agency. *Review of Financial Studies, 8*(2), 431–474.

[32] World Intellectual Property Organization, & Luiss Business School. (2025, July). *World intangible investment highlights 2025* (July 2025 edition). Geneva: WIPO. https://doi.org/10.34667/tind.58686

Appendix

A.1 Derivation of Equilibrium Distribution (Proposition 1)

The profit functions for each project type in each state are:

Tangible Project:

$$\pi_T^\theta = p^\theta q_T - C(q_T) = p^\theta(q_{ind} + \epsilon) - (k + \gamma_T(q_{ind} + \epsilon))(q_{ind} + \epsilon)$$

Intangible Project:

$$\pi_{IA}^S = p^S(q_{ind} + y) - (k + \gamma_{IA}(q_{ind} + y))(q_{ind} + y)$$
$$\pi_{IA}^F = p^F q_{ind} - (k + \gamma_{ind} q_{ind}) q_{ind}$$

Industry prices in each state:

$$p^S = a - b[f(q_{ind} + y) + (n - f)(q_{ind} + \epsilon)]$$
$$p^F = a - b[f q_{ind} + (n - f)(q_{ind} + \epsilon)]$$

Equilibrium condition:

$$\frac{1}{2}(\pi_{IA}^S + \pi_{IA}^F) - I_{IA} = \frac{1}{2}(\pi_T^S + \pi_T^F) - I_T$$

Solving this yields the expression for f^* in Proposition 1.

A.2 Proof of Cash Flow Ordering (Lemma 1)

The profit ordering follows from the competitive price adjustment mechanism and output differences:

$\pi_{IA}^S > \pi_T^S$: In the success state, intangible firms produce more output ($q_{ind} + y > q_{ind} + \epsilon$) with lower marginal costs ($\gamma_{IA} < \gamma_T$).

$\pi_T^S > \pi_T^F$: Tangible firms face higher prices in failure state ($p^F > p^S$).

$\pi_T^F > \pi_{IA}^F$: In failure, intangible firms produce less output ($q_{ind} < q_{ind} + \epsilon$) with higher marginal costs ($\gamma_{ind} > \gamma_T$).

A.3 Mean-Preserving Spread Property (Proposition 2)

Define net cash flows as:

$$\tilde{\pi}_P^\theta = \pi_P^\theta - I_P$$

The equilibrium condition ensures:

$$\frac{1}{2}(\tilde{\pi}_{IA}^S + \tilde{\pi}_{IA}^F) = \frac{1}{2}(\tilde{\pi}_T^S + \tilde{\pi}_T^F)$$

From Lemma 1: $\tilde{\pi}_{IA}^S > \tilde{\pi}_T^S$ and $\tilde{\pi}_{IA}^F < \tilde{\pi}_T^F$. This satisfies the Rothschild-Stiglitz definition of a mean-preserving spread.

A.4 Debt-Investment Choice Interaction (Proposition 3)

For debt level D, equity values are:

$$E(D, T) = \frac{1}{2}[\max(\pi_T^S - D, 0) + \max(\pi_T^F - D, 0)] - I_T$$
$$E(D, IA) = \frac{1}{2}[\max(\pi_{IA}^S - D, 0) + \max(\pi_{IA}^F - D, 0)] - I_{IA}$$

Critical debt levels follow from Lemma 1's profit rankings, determining the intervals in Proposition 3.

A.5 Table 5: GMM Estimates & OLS for Concentrated Industries

Table 5: OLS and System GMM Results for Concentrated Industries

	Ordinary Least Squares			System GMM		
	Leverage	Cash flow volatility	IP	Leverage	Cash flow volatility	IP
Dependent variables						
Intangible portfolio	-0.009**	0.000		-0.128	-0.010	
	(0.004)	(0.001)		(0.230)	(0.014)	
Cash flow volatility	0.055*		-0.058	0.362		-0.016
	(0.029)		(0.051)	(1.311)		(1.316)
Leverage		0.000	0.033**		0.026	0.086
		(0.002)	(0.015)		(0.020)	(0.132)
Instrument variables						
Natural Hedge	-0.018	0.003	-0.023	-0.063	-0.006	-0.355*
	(0.012)	(0.003)	(0.021)	(0.201)	(0.022)	(0.215)
Profitability	0.109***	0.017***	0.056***	0.028	0.036**	0.109
	(0.009)	(0.002)	(0.016)	(0.074)	(0.016)	(0.077)
Size: log(at)	-0.026***	-0.026***	0.038**	0.027	-0.012	-0.121***
	(0.009)	(0.002)	(0.015)	(0.093)	(0.010)	(0.027)
Tobin's q	-0.009***	-0.000	0.001	-0.005	-0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.010)	(0.000)	(0.003)
Collateral ratio	0.138***	-0.069***	-0.061*	-0.047	-0.054*	-0.049
	(0.020)	(0.005)	(0.035)	(0.121)	(0.030)	(0.057)
HHI	-0.033	0.013	-0.081	0.004	0.000	-0.139*
	(0.040)	(0.010)	(0.069)	(0.040)	(0.009)	(0.082)
Observations	18821	18821	18821	18821	18821	18821
Adjusted R^2/Wald χ^2	0.020	0.021	0.002	4.390	5.000	5.360
Hansen J-statistic (χ^2, df = 6)		n/a		6.460	7.000	2.520
AR(2) p-value		n/a		0.203	0.933	0.082

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.6 Table 6: GMM Estimates for Full Sample

Table 6: System GMM Results: Leverage, Risk, and Intangible Positioning

	(1) D_lev_book	(2) D_cfv	(3) D_ip
L1_D_ip	0.006	-0.005	
	(0.113)	(0.011)	
L1_D_cfv	3.778		-0.658
	(3.644)		(0.800)
L1_D_nh	-0.157	-0.019	-0.027
	(0.145)	(0.015)	(0.150)
L1_D_prof	0.158	-0.008	0.000
	(0.206)	(0.027)	(0.145)
L1_D_lnat	0.027	-0.004	-0.089***
	(0.074)	(0.008)	(0.021)
L1_D_q	-0.003	-0.000	0.002
	(0.010)	(0.000)	(0.003)
L1_D_collateral_r	-0.007	-0.030	-0.067
	(0.114)	(0.027)	(0.048)
L1_D_hhi	-0.040	0.007	-0.122
	(0.081)	(0.019)	(0.076)
L1_D_lev_book		-0.072	-0.037
		(0.077)	(0.317)
Constant	0.030**	-0.003**	-0.002
	(0.013)	(0.001)	(0.004)
Observations	36560	36560	36560
Wald ^{2}/F-test	4.470	12.130	5.450
Hansen J-statistic (^{2}, df = 6)	5.390	1.790	2.690
AR(2) p-value	0.340	0.264	0.003

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$