



SCHOOL OF  
ECONOMICS AND  
MANAGEMENT

Master's Thesis in Accounting and Finance

# **Collateral Capacity and the Pricing of Corporate Leverage Risk**

*Evidence from CDS Markets*

Victor Damberg & Jonatan Svanbom

BUSN79 Degree Project in Accounting and Finance

Supervisor: Diem Nguyen

Examiner: Reda Moursli



## **Abstract**

**Seminar Date:** 2026-06-04

**Course:** BUSN79, Degree Project in Accounting and Finance

**Authors:** Victor Damberg, Jonatan Svanbom

**Advisor/Examiner:** Diem Nguyen & Reda Moursli

**Five keywords:** CDS Spreads, Leverage, Asset Tangibility, Financial Distress Risk, Redeployability

**Purpose:** To investigate whether asset tangibility weakens the positive association between leverage and market-implied financial distress risk.

**Methodology:** The empirical analysis uses panel regressions based on firm-level accounting and CDS data from S&P Capital IQ. The preferred specification applies firm and year fixed effects with one-year lagged explanatory variables. Additional analyses include pooled OLS, random effects, redeployability extensions, propensity-score matching, and robustness tests using net leverage and Altman's Z-score.

**Theoretical perspectives:** The theoretical framework consists of trade-off theory, structural credit-risk theory, collateral-channel arguments, and liquidation-value theory.

**Empirical foundation:** The sample consists of publicly listed firms in manufacturing-related sectors between 2015-2024. The final baseline sample includes 4,738 firm-year observations across 832 firms.

**Conclusions:** The study finds strong evidence that leverage is positively associated with CDS spreads, indicating that credit markets consistently price leverage as a source of financial distress risk. However, asset tangibility does not significantly weaken this relationship in the preferred fixed-effects specification, suggesting that broad accounting-based measures of tangibility may not fully capture the collateral channel reflected in CDS pricing.

## **Acknowledgments**

We would like to express our gratitude to our supervisor, Diem Nguyen, for valuable guidance, constructive feedback, and support throughout the thesis process. We would also like to thank Lund University School of Economics and Management for providing a great academic environment during our studies. Finally, we would like to thank our fellow students for the shared experiences during this academic year. The thesis process has been both challenging and rewarding, and we are grateful for everything we have learned along the way.

Lund, May 27, 2026

*Victor Damberg*

*Jonatan Svanbom*

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## **1. Introduction**

### **1.1 General background**

The relationship between leverage and financial distress risk has long been central to corporate finance research (Graham et al., 2015). Debt creates fixed contractual claims, reduces financial flexibility, and increases the probability that adverse shocks translate into financial distress. In trade-off theory, debt is valuable only until the marginal tax and disciplinary benefits are outweighed by expected distress costs (Modigliani & Miller, 1963; Bradley et al., 1984; Myers, 1984). Structural credit-risk theory suggests that higher leverage increases the likelihood of distress as the firm's asset value moves closer to the face value of debt (Merton, 1974). Leverage therefore affects both firm risk and the pricing of credit risk. Yet the consequences of debt are unlikely to be identical across firms. Debt differs in maturity, seniority, covenant structure, and claim priority, and firms with similar leverage ratios may face different credit-market assessments because the assets behind the balance sheet differ (Rauh & Sufi, 2010). A firm with assets that can be pledged, repossessed, and redeployed in distress offers creditors a different recovery profile than a firm whose value rests mainly on intangible capital, organizational know-how, or growth options (Myers, 1977). Two firms may therefore report the same debt ratio while exposing credit markets to different downside losses. The debt ratio is easily observed, whereas the recovery value embedded in the firm's asset base is far less transparent.

This raises the question of whether leverage is priced differently when firms possess more tangible and potentially collateralizable asset bases. If tangible assets improve expected recovery prospects in distress, leverage may not impose identical credit-risk consequences across firms with different asset structures. Credit default swap (CDS) spreads provide a useful setting for examining this issue because they reflect forward-looking market assessments of corporate credit risk.

Manufacturing-related sectors provide a particularly relevant setting for the analysis. Tangible operating assets are meaningful in manufacturing, and the theoretical arguments surrounding collateral, liquidation value, repossession, and redeployability are more credible in this setting than in sectors dominated by intangible capital (Shleifer & Vishny, 1992; Campello & Giambona, 2013). Property, plant, machinery, production facilities, inventories,

and other physical operating assets are central to many manufacturing business models. Yet manufacturing assets differ in salability, specificity, and expected liquidation value. Some assets are standardized and transferable, while others are highly specialized, location-specific, or embedded in narrow production processes. This makes manufacturing a useful setting for studying whether the asset base affects how credit markets price leverage.

## **1.2 Problematization**

A large part of the capital structure literature treats tangibility as a determinant of debt capacity. Firms with more tangible assets are expected to borrow more because such assets are easier to verify, pledge, seize, and sell. This interpretation is supported by broad empirical evidence showing that tangibility is among the most reliable correlates of leverage (Rajan & Zingales, 1995; Frank & Goyal, 2009). It is also consistent with collateral-channel models in which pledgeable assets relax financing constraints and expand feasible borrowing capacity (Almeida & Campello, 2007). Still, the implications for credit risk are less clear.

The same collateral capacity that may protect creditors by improving recovery values can also support higher leverage in the first place. Tangible assets may therefore operate through two opposing channels. On one side, collateral can reduce expected losses in distress by increasing recoverable value. On the other, greater borrowing capacity may allow firms to sustain larger debt burdens, potentially increasing the amount of financial risk that must be priced by credit markets. The observed price of credit risk instead reflects the joint outcome of a risk-increasing leverage channel and a potentially risk-mitigating recovery channel. A simple negative relation between tangibility and CDS spreads would therefore not be sufficient evidence that tangible assets make leverage safer. The more important question is whether the relationship between leverage and credit risk weakens when firms possess assets with greater collateral capacity.

The ambiguity becomes even more difficult to resolve because standard accounting measures of tangibility may not fully capture the type of recoverability that matters in distress. Net property, plant, and equipment scaled by total assets is transparent and widely used, but physical asset intensity is not necessarily equivalent to economically realizable collateral value. Assets recorded under the same accounting category may differ substantially in resale potential, specificity, and liquidation value. A standardized machine with an active secondary market is fundamentally different from highly specialized equipment embedded in one

production process. Liquidation-value research strongly emphasizes this distinction: assets matter for financing because they preserve value outside the current firm, not merely because they are physical in an accounting sense (Shleifer & Vishny, 1992; Benmelech et al., 2005).

Empirical evidence may also overstate the protective role of tangibility. Firms with high tangibility often differ systematically from low-tangibility firms in ways that extend beyond collateral capacity alone. They may operate in more stable industries, maintain different creditor relationships, face different operating risks, or possess more predictable cash-flow structures (Frank & Goyal, 2009). Cross-sectional regressions may therefore capture persistent differences between firms rather than a genuine within-firm collateral relationship (Lemmon et al., 2008). This is essential because cross-sectional and within-firm estimations identify different sources of variation and may therefore imply different interpretations of how tangibility relates to the pricing of credit risk.

The research problem is therefore not whether tangible firms borrow more, nor whether leverage generally increases financial distress risk. Both relationships are already well established in the literature (Frank & Goyal, 2009; Ericsson et al., 2009). The unresolved issue is whether credit markets price leverage as less distress-inducing when it is backed by assets that are more recoverable in downside states, or whether tangibility mainly reflects stable firm characteristics that credit markets already recognize independently of collateral value itself.

### **1.3 Purpose and research question**

The purpose of this thesis is to empirically examine whether asset tangibility dampens the market pricing of leverage-induced financial distress risk. The analysis focuses on publicly listed manufacturing-related sectors with available CDS and accounting data during 2015-2024.

The main research question is: *Does asset tangibility weaken the positive association between leverage and market-implied financial distress risk?*

The thesis addresses the question through three related empirical tests. First, it tests whether leverage is positively associated with CDS spreads, as predicted by trade-off theory and

structural credit-risk models. Second, it tests whether the interaction between leverage and tangibility is negative, which would indicate that the marginal risk effect of leverage is weaker for firms with more tangible assets. As an extension, it examines whether the collateral channel is more visible when tangibility is adjusted for asset redeployability.

#### **1.4 Empirical setting and methodology**

The empirical analysis uses firm-level accounting and CDS data from S&P Capital IQ for listed firms in manufacturing-related sectors between 2015 and 2024. The analysis applies panel regression models to examine whether tangibility weakens the positive association between leverage and market-implied financial distress risk. The preferred specification uses firm and year fixed effects with one-year lagged explanatory variables in order to focus on within-firm variation over time while controlling for common credit-market conditions.

The empirical findings provide strong evidence that leverage is positively associated with CDS spreads across the main specifications. Credit markets therefore appear to treat leverage as an important determinant of financial distress risk. The evidence related to tangibility is considerably less clear. Although some specifications produce negative interaction estimates, the preferred fixed-effects CDS models provide no statistically significant evidence that tangibility weakens the pricing of leverage risk. Additional analyses based on redeployability and high-leverage settings provide some support for collateral-related channels, but the evidence remains limited and sensitive to specification choices.

The thesis contributes to the literature in three main ways. First, it shifts attention from leverage levels themselves toward how credit markets price leverage-related distress risk. Rather than treating tangibility primarily as a determinant of debt capacity, the analysis examines whether leverage appears less risky when firms possess more tangible asset bases. Second, the thesis uses CDS spreads as a forward-looking market measure of financial distress risk rather than relying solely on accounting-based distress proxies. Third, the analysis questions whether raw accounting tangibility adequately captures realizable collateral value by distinguishing between the quantity of tangible assets and their potential recoverability in distress situations.

## **1.5 Outline**

The remainder of the thesis is organized as follows. Section 2 reviews the relevant theoretical and empirical literature and develops the hypotheses. Section 3 presents the empirical methodology, including the baseline fixed effects model, benchmark models, robustness tests, redeployability extension, and methodological limitations. Section 4 describes the data, sample construction, variables, and descriptive-statistics approach. Section 5 presents and discusses the empirical findings, including the main regression results, interpretations, and robustness analyses. Section 6 concludes the thesis and discusses limitations as well as directions for future research.

## **2. Literature Review and Hypothesis Development**

### **2.1 Traditional theories of capital structure and distress risk**

The theoretical starting point is the irrelevance proposition of Modigliani and Miller (1958), under which financing choices do not affect firm value in perfect capital markets. Once the assumptions of perfect markets are relaxed, capital structure becomes economically meaningful. Taxes, bankruptcy costs, agency conflicts, asymmetric information, and financing frictions create reasons why capital structure can affect firm value and risk (Modigliani & Miller, 1963; Harris & Raviv, 1991).

The trade-off theory is particularly relevant for this analysis. Debt can create value through the tax deductibility of interest payments (Modigliani & Miller, 1963; Graham, 2000). Yet, debt also increases expected costs of financial distress. Firms in turn face an optimal financing problem: debt is valuable up to the point where marginal debt benefits are offset by marginal expected distress costs (Bradley et al., 1984; Myers, 1984). Empirical evidence suggests that default and distress are costly in market-value terms, not merely legal events (Andrade & Kaplan, 1998; Davydenko et al., 2012)

Structural credit-risk theory links these capital structure arguments directly to market pricing. In Merton (1974), corporate debt is a contingent claim on firm assets, and default occurs when asset value falls below promised debt payments (Bharath & Shumway, 2008). The core prediction is: credit risk depends on leverage, asset value, and asset volatility. Higher

leverage reduces the distance between asset value and debt obligations and should in turn be associated with higher credit spreads.

## **2.2 Tangibility, collateral, and borrowing capacity**

Asset tangibility is one of the most established firm-level determinants of capital structure. Rajan and Zingales (1995) show that firms with more tangible assets tend to carry more debt across major industrialized countries. Frank and Goyal (2009) similarly identify tangibility as one of the most reliable factors explaining leverage. The common explanation is collateral, tangible assets are easier to observe, value, pledge, and seize than intangible assets. They reduce creditor losses in default and consequently support debt financing.

Almeida and Campello (2007) provide a central contribution to the collateral channel by showing how pledgeable assets affect borrowing capacity and investment under financing constraints. Their argument is not simply that tangible firms borrow more. It is that collateral expands the set of feasible financing arrangements. When lenders can rely on assets as security, external finance becomes less restrictive.

However, the debt-capacity literature does not automatically imply that tangibility lowers market-priced distress risk. A firm may borrow more because it has collateral. If the additional debt consumes the safety created by collateral, the net effect on credit risk is vague. This distinction also motivates the main research question. Rather than asking whether tangibility explains leverage, the thesis asks if tangibility moderates the risk consequence of leverage.

## **2.3 Liquidation value and asset redeployability**

The liquidation-value literature refines the collateral argument by emphasizing that collateral only matters if it can preserve value in distress. Shleifer and Vishny (1992) argue that liquidation values depend heavily on the financial condition of potential buyers. When distress affects an entire industry, buyers may also face financial pressure, causing assets to sell below their value in best use. In practice, assets can become least liquid precisely when firms need liquidity the most.

Benmelech et al. (2005) provide evidence that asset redeployability affects financial contracts directly. Assets that are easier to redeploy support larger loans, longer maturities, lower borrowing costs, and fewer creditors. Eisfeldt and Rampini (2009) reach a similar conclusion,

showing that repossession and control rights matter for debt capacity because assets that can be more easily seized and reused support greater financing. Campello and Giambona (2013) extend this argument to corporate balance sheets and show that the salability of real assets matters for capital structure beyond conventional tangibility measures. Kim and Kung (2017) further develop industry-level redeployability measures by examining how transferable and reusable productive assets are across industries. Their framework highlights that collateral value depends not only on the existence of tangible assets, but also on whether those assets can realistically be reused outside the current firm or industry.

This perspective is especially relevant in manufacturing-related sectors. Two firms may report similar net PPE ratios while offering very different recovery prospects in distress. Warehouses, vehicles, and standardized machinery are generally easier to resell or transfer than highly specialized production equipment designed for one specific use. Raw tangibility may thus miss valuable differences in collateral quality. If recovery value matters for how credit markets price leverage, the leverage-mitigating effect of tangibility should be stronger when tangible assets are more redeployable.

## **2.4 CDS spreads and market-implied credit risk**

Financial distress risk can be measured in several ways. Accounting-based models, such as Altman's Z-score, use financial ratios to estimate bankruptcy risk (Altman, 1968). Market-based approaches use equity prices, bond yields, or credit derivatives to infer default risk (Campbell & Taksler, 2003). This thesis uses CDS spreads as the main dependent variable because CDS contracts are directly linked to the price of protection against default. A higher CDS spread indicates that the market requires a higher premium to bear the firm's default risk

CDS spreads have several advantages for this research question. They are forward-looking, continuously updated, and directly tied to credit events. Blanco et al. (2005) provide evidence that CDS markets play an essential role in credit-risk price discovery. Longstaff et al. (2005) use CDS data to separate default and non-default components of corporate spreads and show that default risk accounts for a substantial share of spread levels. Ericsson et al. (2009) find that leverage, volatility, and the risk-free rate are important determinants of CDS premia.

Zhang et al. (2009) further show that equity volatility and jump risk explain substantial variation in CDS spreads even after accounting for balance-sheet information.

At the same time, CDS spreads are not a pure measure of bankruptcy probability. They are affected by liquidity, counterparty considerations, contract conventions, risk premia, and common market factors (Blanco et al., 2005; Longstaff et al., 2005). This is why the thesis uses the natural logarithm of CDS spreads, includes year fixed effects, and addresses these measurement limitations directly in the empirical design. CDS spreads are not interpreted as perfect measures of default probability, but rather to examine whether leverage, tangibility, and their interaction help explain variation in market-priced credit risk after accounting for firm and year effects.

## **2.5 Hypothesis motivation and empirical tensions**

The role of tangibility in credit markets is not entirely clear. Tangible assets may improve recovery values in distress and reduce expected creditor losses. At the same time, firms with greater collateral capacity are often able to sustain higher leverage. In practice, the additional borrowing capacity created by collateral may partly offset the safety benefit associated with tangible assets. This creates a distinction between debt capacity and market-priced credit risk. A firm with more tangible assets may be able to borrow more without necessarily being perceived as safer by CDS markets. More relevant is whether CDS markets assess leverage differently when firms hold more recoverable assets. For this reason, the interaction between leverage and tangibility is more informative than the standalone tangibility coefficient.

There are also clear measurement limitations. Net PPE scaled by total assets is widely used in the capital-structure literature and has the advantage of being observable and comparable across firms. Still, it remains a fairly rough proxy for collateral quality. Book values may not reflect actual liquidation values, depreciation practices differ across firms, and accounting measures reveal little about resale markets, asset specificity, or pledgeability in distress (Campello & Giambona, 2013).

This issue is particularly relevant in CDS markets, where investors may price broader recovery expectations rather than accounting-based asset composition alone. The redeployability extension partly addresses this by incorporating differences in expected asset salability across sectors. Even so, redeployability is difficult to measure precisely and varies

only modestly within firms over time. Consequently, this extension serves to provide exploratory insights into asset salability rather than establishing strict causal links.

### **2.5.1 Leverage and distress risk**

The first hypothesis follows from trade-off theory and structural credit-risk models. Higher leverage increases fixed financial obligations and leaves firms with less financial flexibility during periods of stress. It also reduces the distance between firm value and promised debt payments, making default more likely when firm value deteriorates. From a credit-market perspective, more leverage should thus be associated with higher compensation for bearing default risk.

H1: Leverage is positively associated with market-implied financial distress risk.

### **2.5.2 Tangibility as a moderator of leverage risk**

The second hypothesis focuses on whether collateral capacity affects how CDS markets price leverage risk. If tangible assets improve expected recovery values in distress, the risk effect of leverage may be weaker when debt is backed by a larger tangible asset base. In that case, creditors may view highly leveraged firms as less risky when a greater share of assets can potentially be recovered or pledged.

Firms with more tangible assets are often also able to sustain higher leverage, which may offset part of the reduction in expected distress costs. The empirical effect is thus ultimately unclear beforehand. Even so, if collateral quality matters for market-priced credit risk, the interaction between leverage and tangibility is expected to be negative in the CDS setting.

H2: Asset tangibility weakens the positive association between leverage and market-implied financial distress risk.

### **2.5.3 Redeployability and collateral quality**

As an exploratory extension, the thesis examines whether the interaction between leverage and tangibility becomes stronger when tangibility is conditioned on sector-level asset redeployability. The idea is that collateral value depends not only on the existence of tangible assets, but also on how easily those assets can be transferred, resold, or reused outside the firm.

Two firms may report similar levels of net PPE while facing very different expected recovery values in distress. Standardized machinery or generic industrial equipment may be easier to sell than highly specialized production assets tied to a narrow use case. If CDS markets care about expected recovery values, the moderating effect of tangibility may consequently be more visible when assets are more redeployable.

At the same time, redeployability is difficult to measure precisely and varies only modestly within firms over time. Hence, this analysis provides valuable insights into asset quality, though it does not represent a definitive causal test.

### **3. Methodology**

The empirical analysis combines panel-regression models, extensions, and robustness tests to examine how leverage, tangibility, and collateral quality relate to market-implied distress risk. The baseline analysis uses firm fixed effects with year fixed effects to estimate whether tangibility moderates the relationship between leverage and CDS spreads. Pooled OLS and random-effects specifications are reported as benchmark models and compared to the preferred fixed-effects framework. The analysis further includes an exploratory redeployability extension, a high-leverage heterogeneity test, and several robustness checks using alternative leverage definitions and distress-risk measures.

#### **3.1 Baseline panel regression**

The baseline empirical model estimates the association between leverage, tangibility, their interaction, and market-implied distress risk using firm-year panel data. The dependent variable is the natural logarithm of the five-year CDS par spread mid. The main explanatory variables are lagged leverage, lagged tangibility, and their interaction. The baseline specification includes profitability, firm size, firm age and Tobin's Q as control variables. These variables are included because prior literature suggests that profitability, growth opportunities and firm scale may influence both capital structure decisions and market-implied distress risk (Ericsson et al., 2009). The model includes firm fixed effects and year fixed effects.

Formally, the baseline specification is:

$$\ln(CDS_{i,t}) = \beta_1 Leverage_{i,t-1} + \beta_2 Tangibility_{i,t-1} + \beta_3 (Leverage_{i,t-1} \times Tangibility_{i,t-1}) + \beta_4 Size_{i,t-1} + \beta_5 Profitability_{i,t-1} + \beta_6 Age_{i,t-1} + \beta_7 Tobins\ Q_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t}$$

**Where:**

|                         |                                                                        |
|-------------------------|------------------------------------------------------------------------|
| $\ln(CDS_{i,t})$        | is the five-year CDS par spread mid for firm $i$ in year $t$           |
| $Leverage_{i,t-1}$      | is total debt divided by total assets                                  |
| $Tangibility_{i,t-1}$   | is net PPE divided by total assets                                     |
| $Size_{i,t-1}$          | is the natural logarithm of total assets                               |
| $Profitability_{i,t-1}$ | is EBIT divided by total assets                                        |
| $Age_{i,t-1}$           | is the natural logarithm of firm age                                   |
| $Tobin's\ Q_{i,t-1}$    | is the ratio of market value of equity plus total debt to total assets |
| $\alpha_i$              | denotes firm fixed effects                                             |
| $\delta_t$              | denotes year fixed effects                                             |
| $\epsilon_{i,t}$        | is the error term                                                      |

The coefficient of primary interest is  $\beta_3$ . A negative  $\beta_3$  indicates that the positive association between leverage and CDS spreads is weaker when tangibility is higher. In economic terms, this would support the interpretation that collateral capacity mitigates the market pricing of

leverage-induced distress risk. A statistically insignificant coefficient would instead suggest limited evidence that tangibility moderates the leverage-risk relationship within the sample.

### **3.2 Benchmark models and model selection**

The thesis reports pooled OLS and random effects models as benchmarks. Pooled OLS provides a combined cross-sectional and time-series association without controlling for unobserved firm heterogeneity. Random effects allow firm-specific components but rely on the assumption that the unobserved firm effect is uncorrelated with the explanatory variables. This assumption is demanding since leverage, asset structure, profitability, and credit risk are all likely related to persistent firm characteristics.

A Hausman test is used to evaluate whether the random-effects estimator is consistent relative to fixed effects (Hausman, 1978). The Hausman test reported in Table 7 strongly rejects the random-effects assumption ( $p < 0.001$ ), indicating that the unobserved firm effects are correlated with the explanatory variables. This supports the use of firm fixed effects as the preferred specification.

### **3.3 Standard errors and inference**

Standard errors are clustered at the firm level. This choice follows the panel structure of the data and reflects the fact that residuals are unlikely to be independent within firms over time. In corporate finance panels, firm-year observations are often serially related because capital structure, profitability, asset composition, and credit risk evolve gradually rather than independently from one year to the next. Ignoring this dependence may lead to understated standard errors and overly confident inference. Petersen (2009) shows that standard-error choices can affect inference in finance panels. Firm-level clustering hence provides a more conservative and appropriate basis for statistical testing.

The thesis also examines heteroskedasticity and multicollinearity diagnostics. The diagnostic tests reported in Table 7 indicate clear evidence of heteroskedasticity. White's test rejects the null of homoskedasticity, and the modified Wald test for groupwise heteroskedasticity in the fixed-effects model is also statistically significant. This supports the use of robust

firm-clustered standard errors in the main specifications. If heteroskedasticity is present and conventional standard errors are used, significance levels may be misleading.

Multicollinearity is also assessed using variance inflation factors. As reported in Table 7, the mean VIF is 2.91 which does not indicate severe multicollinearity. The highest VIF values occur for the interaction-related variables, which is expected given the relationship between interaction terms and their underlying components. Although the highest VIF reaches 9.69, the mean VIF remains low and does not suggest severe multicollinearity concerns for the empirical analysis. It does, however, reinforce the need to interpret interaction coefficients carefully, since product terms require sufficient independent variation in both the underlying variables and their interaction. Accounting for this limited precision, the empirical analysis focuses primarily on the direction, statistical significance, and economic interpretation of the coefficients across specifications.

### **3.4 Redeployability extension**

The redeployability extension examines whether the collateral channel becomes stronger when tangible assets are more redeployable and hence potentially retain greater value in distress. The extension builds on the idea that tangible assets protect creditors only if they can realistically be transferred, resold, or reused outside the current firm (Shleifer & Vishny, 1992; Kim & Kung, 2017). To capture this, the analysis introduces a redeployability-adjusted specification based on a triple interaction between leverage, tangibility, and sector-level redeployability. The purpose is to examine whether the moderating effect of tangibility on the leverage-distress relation becomes stronger when assets are expected to be more redeployable.

Formally, redeployability is measured at the sector level and interacts with the baseline leverage-tangibility specification. The triple interaction thus tests whether the pricing of leverage risk differs not only with the amount of tangible assets, but also with the expected salability and reuse potential of those assets.

The test does not warrant a strong causal interpretation. Since redeployability is assigned at the sector level and changes little over time, much of its variation is absorbed by firm fixed effects. The extension thus asks whether the collateral channel appears stronger when tangible assets are weighted by expected salability, even within a demanding fixed-effects

setting. The redeployability analysis therefore provides suggestive evidence of these within-firm dynamics.

### **3.5 Propensity-score matching analysis**

The thesis further examines whether collateral-related characteristics become more relevant when leverage is high and financial distress risk becomes more salient. The intuition is that recovery value should matter more once firms operate closer to distress (Shleifer & Vishny, 1992). At relatively low leverage levels, creditors may place less weight on collateral value because firms operate further from default. As leverage increases, however, expected recovery values may become increasingly relevant for credit pricing.

To explore this possibility, the analysis implements a propensity-score matching (PSM) procedure within the high-leverage portion of the sample, defined as firms with leverage ratios above the sample median. High-tangibility firms are matched to otherwise comparable low-tangibility firms using one-to-one nearest-neighbor matching with common support based on lagged firm characteristics.

The purpose of the matching design is to reduce observable differences between firms and examine whether collateral-related characteristics remain associated with differences in CDS spreads among highly levered firms. The matching analysis is interpreted as a complementary robustness exercise rather than as a replacement for the baseline panel regressions. Unlike the fixed-effects specifications, which rely on within-firm variation over time, the matching framework compares firms with similar observable characteristics across groups. This provides an additional perspective on whether collateral capacity appears more relevant when leverage-related distress risk is likely to matter more strongly.

### **3.6 Alternative distress-risk measures, net leverage and non-lagged specifications**

To assess whether the findings are sensitive to the choice of distress-risk proxy, the thesis additionally estimates a supplementary specification using Altman's Z-score, a traditional accounting-based measure of financial distress developed for manufacturing firms (Altman, 1968).

The measure should therefore be viewed as a complementary accounting-based proxy for financial distress rather than as a direct substitute for market-implied CDS pricing. This

distinction is particularly important in a globally diversified sample where accounting environments, sector composition, and bankruptcy regimes differ across firms and countries. This robustness test should not be interpreted as equivalent to the CDS regressions, since Altman's Z-score is an accounting-based measure rather than a market-implied credit-risk measure.

A further robustness test replaces gross leverage with net leverage, defined as total debt minus cash divided by total assets. Net leverage accounts for the fact that cash holdings reduce effective debt burden. Two firms with the same gross leverage may differ substantially in financial flexibility if one holds more cash. If the main findings remain similar under net leverage, the results are less likely to be driven by liquidity differences hidden inside gross debt ratios.

The thesis also estimates a contemporaneous specification using non-lagged explanatory variables. While the baseline regressions use one-year lagged accounting variables to impose temporal ordering between firm characteristics and subsequent CDS pricing, the non-lagged specification examines whether the main findings depend materially on the lag structure of the model. Although contemporaneous regressions introduce greater simultaneity concerns, they provide an additional robustness check regarding the stability of the estimated relationships.

### **3.7 Methodological limitations**

The empirical design is subject to endogeneity concerns. Leverage, tangibility, profitability, and CDS spreads are jointly related through firms' financing decisions, operating conditions, and changing market expectations. Firms do not choose capital structures randomly, and credit markets continuously update the pricing of distress risk as new information becomes available (Blanco et al., 2005; Norden & Weber, 2004). A firm experiencing deteriorating operating prospects or rising expected default risk may simultaneously adjust leverage, investment, liquidity management, or asset composition, while CDS investors revise required credit protection premia at the same time.

The interaction between leverage and tangibility introduces an additional identification challenge. Firms with stronger collateral capacity are often able to sustain higher leverage precisely since creditors expect greater recovery potential in distress. In this setting, leverage

and collateral capacity may evolve jointly and not independently. The estimated interaction term as a result reflects an equilibrium relationship between debt capacity, expected recovery value, and market-priced credit risk rather than a clean causal collateral effect.

The empirical design addresses some of these concerns. Firm fixed effects absorb persistent differences in business models, operating risk, asset structure, and long-run financing policies, while year fixed effects control for common macroeconomic and credit-market conditions. The use of one-year lagged explanatory variables also reduces immediate simultaneity between accounting characteristics and CDS pricing. Even so, the analysis does not establish strict causal identification. Unobserved time-varying factors may still affect both firms' balance-sheet decisions and market-implied distress risk. The results should thus be interpreted as conditional associations within the observed CDS-market setting, as opposed to definitive causal effects.

The second limitation is measurement. Tangibility is a rough proxy for collateral capacity. Net PPE does not reveal asset specificity, legal pledgeability, liens, seniority, liquidation discounts, or the financial condition of potential buyers. Not all tangible assets provide the same recovery value (Kim & Kung, 2017). Standardized machinery differs fundamentally from highly specialized production equipment. Credit markets likely price expected recovery using information that extends beyond balance-sheet PPE intensity alone (Campello & Giambona, 2013). Debt seniority, covenant structure, secured borrowing, asset-market liquidity, geographic concentration, and refinancing conditions may all matter. The redeployability extension improves the framework conceptually, but it does not fully solve the measurement problem.

The third limitation is sample selection. CDS coverage is concentrated among larger and more credit-market-visible firms. This is appropriate for studying market-priced credit risk, but it limits external validity. The findings speak primarily to listed firms in manufacturing-related sectors with observable CDS contracts. They should not be generalized to smaller private firms, firms without traded credit instruments, or sectors where intangible assets dominate value creation.

The fourth limitation concerns the interaction design. Interaction models are statistically demanding. The leverage-tangibility interaction is by definition related to its components, and tangibility changes slowly over time. Firm fixed effects improve credibility by absorbing

persistent unobserved firm characteristics, but they also remove much of the cross-sectional variation through which collateral capacity may operate. Pooled models may better capture structural differences across firms, while fixed-effects models provide a more demanding test of whether within-firm changes in tangibility alter the pricing of leverage risk. The thesis thus provides evidence on market pricing within this empirical setting, while also illustrating the empirical difficulty of isolating a distinct collateral channel in CDS markets.

These limitations should be considered when interpreting the results. The thesis examines how credit markets price leverage when observable CDS-market pricing is available. The sample construction is thus aligned with the study's focus on market-priced distress risk, even though it narrows the scope of the conclusions.

## **4. Data and Variable Construction**

### **4.1 Data sources and sample selection**

The empirical analysis is based on firm-level accounting and market data from S&P Capital IQ. The sample consists of publicly listed firms across all geographic regions over the period 2015-2024. The analysis focuses on firms classified within manufacturing-related sectors: Industrials, Consumer Discretionary, Materials, and Consumer Staples. Table 3 reports the geographic distribution of the sample, while Table 4 reports the industry-sector composition of the final regression sample. These sectors are selected because their business models rely on tangible productive assets, making them appropriate settings for examining collateral capacity, liquidation value, and asset redeployability. The sample is globally diversified across manufacturing-related sectors, although CDS coverage remains concentrated among larger firms in developed credit markets. The global sample improves generalizability but also introduces heterogeneity in legal systems, bankruptcy procedures, and credit-market structures.

The sample period spans several markedly different credit-market environments. Before 2020, financing conditions were unusually loose, with low interest rates and abundant liquidity. Conditions then shifted rapidly following the Covid-19 shock (Falato et al., 2021; Kargar et al., 2021), the subsequent inflation surge, and aggressive monetary tightening.

Given that the pricing of leverage and collateral capacity is unlikely to remain constant across such different financing conditions, the empirical design includes year fixed effects to absorb common macroeconomic and credit-market shocks across the sample period.

The sample is restricted to firms with observable five-year CDS pricing on 31 December 2024 in order to construct a consistent panel of firms with identifiable CDS-market participation. The filter was applied as a practical data-construction procedure in Capital IQ and does not require continuous CDS availability throughout the sample period. The resulting panel consequently remains unbalanced.

The use of end-of-period CDS availability introduces potential survivorship or sample-selection bias, since firms that disappeared from CDS markets before 2024 are less likely to be included in the sample. The dataset may therefore underrepresent firms experiencing severe distress, restructuring, delisting, or declining CDS-market activity during the sample period. The findings provide distinct insights into market dynamics for firms with a persistent CDS-market presence.

At the same time, CDS coverage is substantially narrower in earlier years of the sample period. Requiring CDS availability at the beginning of the period would materially reduce the sample size and automatically exclude firms that entered CDS markets later over time. Such a restriction would produce a more static panel and potentially underrepresent firms experiencing evolving capital structures or changing credit-market relevance. The chosen filter consequently reflects a trade-off between broader CDS-market coverage and potential sample-selection effects.

The accounting variables used in the empirical analysis are subsequently matched to the CDS observations. Because the preferred specification uses one-year lagged explanatory variables, some firm-year observations are lost when prior-year accounting information is unavailable. Additional reductions in observations occur because not all firms report every accounting variable required for each regression specification.

The data are organized as an unbalanced firm-year panel. The resulting panel is unbalanced because firms enter and exit the sample depending on CDS coverage, accounting-data availability, and the use of lagged regressors. The final baseline regression sample consists of 4,738 firm-year observations across 832 firms. Finally, observations with missing values in the variables required for a given regression are removed through listwise deletion. The

variation in observation counts across models reflects differences in data availability across specifications.

## 4.2 Dependent variables

The main dependent variable is the natural logarithm of the five-year CDS par spread mid. The CDS par spread mid is the midpoint between bid and ask quotes and is measured in basis points. The five-year tenor is used because it is a standard reference point in corporate credit markets and is commonly used in empirical CDS research (Longstaff et al., 2005; Ericsson et al., 2009). Taking the natural logarithm reduces skewness and allows coefficients to be interpreted approximately as percentage changes in CDS spreads for unit changes in the explanatory variables.

CDS spreads are interpreted as market-based measures of financial distress risk. A higher spread means that the market requires greater compensation for bearing default risk on the reference entity. This measure is well aligned with the research question because the thesis studies the market pricing of leverage-induced distress risk rather than realized bankruptcy alone.

An additional robustness specification uses Altman's Z-score as an accounting-based proxy for financial distress. Altman's Z-score combines several accounting ratios related to liquidity, profitability, leverage, solvency, and operating performance (Altman, 1968). Higher Z-scores indicate lower bankruptcy risk. The purpose of this robustness test is not to replace CDS spreads, but to examine whether the baseline findings remain broadly consistent when distress risk is measured using accounting fundamentals rather than market-implied credit pricing. Since Altman's Z-score partly overlaps conceptually with some accounting-based control variables, the results do not warrant a strong causal interpretation and are primarily used as a complementary robustness analysis.

Altman's Z-score is calculated using the original manufacturing-based specification developed by Altman (1968):

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

Where:

$X_1 = \text{Working Capital} / \text{Total Assets}$

$X_2 = \text{Retained Earnings} / \text{Total Assets}$

$X_3 = \text{EBIT} / \text{Total Assets}$

$X_4 = \text{Market Value of Equity} / \text{Total Liabilities}$

$X_5 = \text{Sales} / \text{Total Assets}$

Traditionally, Z-scores above approximately 3 are interpreted as relatively low bankruptcy risk, while values below roughly 1.8 are associated with elevated financial distress risk (Altman, 1968). While these thresholds provide a foundational benchmark, they are evaluated here considering that the original model was calibrated for U.S. manufacturing firms, whereas this study examines a globally diversified sample of listed firms over time.

#### **4.3 Main explanatory variables**

Leverage is defined as total debt divided by total assets. This variable captures the extent to which the firm's asset base is financed by debt. Based on trade-off theory and structural credit-risk models, leverage is expected to be positively associated with CDS spreads.

Tangibility is defined as net property, plant, and equipment divided by total assets. This measure is widely used in capital structure research as a proxy for collateral capacity (Campello & Giambona, 2013). Tangible assets are generally easier to pledge, verify, and potentially recover in distress situations than intangible assets, making them relevant for creditor protection and borrowing capacity.

At the same time, the measure remains imperfect because accounting-based PPE intensity does not necessarily correspond to meaningful collateral value. Prior research emphasizes that different categories of tangible assets may differ substantially in liquidity, salability, and redeployability across firms and industries (Campello & Giambona, 2013). Nevertheless, despite these limitations, PPE scaled by total assets remains the standard empirical proxy for tangibility and collateral capacity because it is observable, broadly comparable across firms, and consistently available across large panel datasets.

The key variable is the interaction between leverage and tangibility. This interaction tests whether the marginal effect of leverage on distress risk depends on the firm's tangible asset

base. A negative coefficient on the interaction term would be consistent with the hypothesis that tangible assets mitigate the market pricing of leverage-induced distress risk

For the redeployability extension, sector-level redeployability measures are constructed using the manufacturing-industry redeployability framework developed by Kim and Kung (2017). Their measure captures the extent to which productive assets can be transferred and reused across firms and industries based on secondary-market asset usability and industry asset composition.

Since the original redeployability classifications are reported at a more granular manufacturing-industry level, the thesis maps these industries into the broader Global Industry Classification Standard (GICS) manufacturing-related sectors used in the empirical sample. Sector-level redeployability values are therefore calculated as averages of the underlying manufacturing-industry redeployability measures within each GICS sector. The resulting redeployability-adjusted tangibility measure is constructed as tangibility multiplied by sector-level redeployability.

This variable captures not only how much tangible capital the firm has, but also how reusable that capital is expected to be outside the current firm. Because redeployability varies primarily across sectors rather than within firms over time, this extension highlights important cross-sectional dynamics rather than aiming for within-firm identification. Table 6 reports the mapping of the original manufacturing-industry redeployability measures from Kim and Kung (2017) into the GICS sector structure used in this thesis.

#### **4.4 Control variables**

The baseline model includes firm size, profitability, firm age and Tobin's Q as control variables. These variables are included to account for observable firm characteristics that may systematically influence both capital structure and market-priced credit risk. Prior capital-structure research identifies firm size, profitability, and market valuation measures as important correlates of leverage decisions, while CDS-spread studies commonly control for firm balance-sheet characteristics when explaining credit spreads (Rajan & Zingales, 1995; Zhang et al., 2009).

Firm size is measured as the natural logarithm of total assets and is expected to be negatively associated with CDS spreads, since larger firms are typically more diversified, more visible

to capital markets, and better able to access external financing. Profitability is measured as EBIT divided by total assets. More profitable firms generate stronger internal cash flows and should therefore face lower debt-servicing pressure, implying a negative expected relation with CDS spreads. Tobin's Q is included as a proxy for growth opportunities and market valuation relative to book assets and is measured as market value of equity plus book value of debt divided by book value of total assets. Its expected sign is ambiguous: higher valuation may signal stronger future prospects and lower expected distress risk, but growth firms may also rely more heavily on intangible assets and exhibit more uncertain cash-flow expectations. Firm age is included to capture differences in organizational maturity, operating history, and long-term survival. Older firms may benefit from more established creditor relationships, greater reputational capital, and more stable operating structures, which could reduce perceived credit risk. Firm age is measured as the natural logarithm of the number of years since firm incorporation, and is consequently expected to be negatively associated with CDS spreads.

The objective is not to estimate a complete credit-risk prediction model, but rather to isolate the conditional relation between leverage, tangibility, and market-priced distress risk while controlling for key observable firm characteristics.

#### **4.5 Data treatment**

All explanatory variables are winsorized at the 1st and 99th percentiles to reduce the influence of extreme observations. Panel data often contain outliers caused by very small denominators, restructuring events, reporting anomalies, or unusual balance-sheet values. Winsorization reduces the risk that a small number of extreme observations drives the results. At the same time, extreme observations may contain genuine distress information. This trade-off necessitates cross-specification robustness tests to ensure that the primary findings are not artifacts of the winsorization threshold.

Consistent with prior empirical CDS literature, the baseline specification uses one-year lagged explanatory variables relative to the dependent variable (Zhang et al., 2009). Lagging the explanatory variables helps reduce contemporaneous simultaneity between accounting characteristics and CDS spreads while imposing temporal ordering between accounting information and market-priced credit risk.

## 4.6 Descriptive statistics

Table 1 reports summary statistics for the main regression sample used in the baseline specifications. The dependent variable, the natural logarithm of the five-year CDS spread, has a mean of 4.589 and a median of 4.477. The relatively small difference between the two values suggests that the logarithmic transformation substantially reduces the strong right-skewness typically present in raw CDS-spread data.

In raw basis-point form, CDS spreads display a substantially wider distribution, with a mean of 149.9 basis points and a median of 88.0 basis points. These levels indicate that the sample primarily consists of firms with moderate but meaningful perceived credit risk rather than firms in immediate financial distress. At the same time, the large gap between the mean and median suggests that a smaller subset of firms exhibits substantially elevated CDS spreads, consistent with periods of heightened financial stress or weaker credit quality.

The maximum CDS spread of roughly 890 basis points further indicates that the sample includes episodes of severe market-implied distress risk, although such observations are relatively rare.

The average lagged leverage ratio is 0.348, while the median is 0.333. Firms in the sample are therefore clearly debt-financed, though not excessively levered on average. The standard deviation of 0.158 indicates meaningful variation in debt intensity across firm-years. Some firms operate with relatively conservative balance sheets, while others rely substantially more on debt financing

Tangibility has a mean of 0.305 and a median of 0.263, indicating that net property, plant, and equipment account for roughly 31% of total assets on average. This is broadly consistent with the manufacturing-oriented composition of the sample, where physical operating assets play an important role in production and financing capacity. At the same time, the substantial dispersion in tangibility indicates that firms differ meaningfully in asset intensity and potential collateral capacity, despite operating within broadly similar sectors.

The control variables largely behave as expected. Profitability has a mean of 0.082 and a median of 0.073, suggesting that most firms in the sample generate positive operating earnings relative to assets. Tobin's Q displays a mean of 1.456 and a median of 1.098, indicating that market values generally exceed book asset values, although with considerable

cross-sectional variation. Firm size, measured as the logarithm of total assets, has a mean of 9.186, while the average firm age exceeds 90 years. The sample therefore primarily consists of relatively large and mature public firms. This is consistent with the structure of CDS markets, which tend to concentrate on larger, more visible firms with active participation in debt capital markets.

Altman's Z-score has a mean of 4.062 and a median of 3.278. Since higher Z-scores indicate lower accounting-based bankruptcy risk, these values place the average sample firm firmly within the safe zone, suggesting that most observations are not in immediate financial distress. Traditionally, Z-scores above approximately 3 are interpreted as relatively low bankruptcy risk, while values below roughly 1.8 are associated with elevated distress risk (Altman, 1968). The distribution is therefore broadly consistent with the structure of CDS markets, which are concentrated among larger and more established listed firms rather than firms already close to bankruptcy.

The pairwise correlations reported in Table 5 provide an initial indication of the expected relationships between the main variables. The correlation between log CDS spreads and leverage is positive and statistically significant (0.285), consistent with the view that more highly levered firms are perceived as riskier by credit markets. Profitability is negatively correlated with CDS spreads (-0.168), suggesting that firms with stronger earnings capacity are viewed as better able to absorb shocks and service debt obligations. Firm size likewise displays a relatively strong negative correlation with CDS spreads (-0.420), indicating that larger firms are generally perceived as financially safer, potentially due to greater diversification, stronger market access, and higher liquidity.

Tangibility, however, is positively correlated with CDS spreads (0.093). This may initially seem counterintuitive, since tangible assets are often associated with stronger collateral capacity and higher expected recovery values. This correlation reflects confounding firm characteristics and not a direct economic link. Firms with more tangible asset bases may also maintain higher leverage ratios or exhibit greater exposure to cyclical downturns within manufacturing-related activities. Simple pairwise correlations therefore cannot isolate the recovery-related driver underlying the collateral hypothesis.

At the same time, tangibility is positively correlated with leverage (0.133), which is itself consistent with capital structure theory suggesting that tangible assets support debt capacity

and borrowing ability. This illustrates the central empirical tension of the thesis. Tangible assets may simultaneously support higher leverage while also potentially improving expected recovery values in distress. The net relation between tangibility and market-implied distress risk is therefore ambiguous already at the descriptive level.

Redeployability is negatively correlated with CDS spreads (-0.215), providing some preliminary indication that more redeployable assets may be associated with lower perceived credit risk. However, the relatively limited variation in redeployability within the manufacturing sample bounds the scope of this economic interpretation.

Overall, the correlations are economically plausible and broadly consistent with the theoretical expectations discussed in the thesis. None of the pairwise correlations among the main explanatory variables appear sufficiently large to indicate severe multicollinearity concerns.

#### **4.7 Univariate comparison across tangibility groups**

Table 2 reports the univariate comparison between firms with high and low tangibility. Firms with higher tangibility exhibit both greater leverage and wider CDS spreads on average, despite holding more collateralizable asset bases. High-tangibility firms display an average leverage ratio of 0.362 compared to 0.335 among low-tangibility firms, while the average log CDS spread is 4.647 versus 4.530. Both differences are statistically significant at the 1 % level.

The economic intuition behind the result is mixed. Firms with more tangible assets appear able to sustain larger debt burdens, consistent with prior collateral-capacity literature emphasizing the role of pledgeable assets in supporting borrowing capacity (Almeida & Campello, 2007). At the same time, these firms also exhibit higher market-implied credit risk on average. This pattern is not fully consistent with a simple distress-cost interpretation of tangibility. The evidence instead suggests that firms with greater collateral capacity may simultaneously sustain higher leverage, potentially offsetting part of the recovery-related benefits associated with tangible assets.

Several additional differences across the groups offer valuable economic insights. High-tangibility firms exhibit lower Tobin's Q ratios (1.357 versus 1.551), weaker Altman Z-scores (3.650 versus 4.458), and slightly lower profitability (0.079 versus 0.086). These

patterns suggest that high-tangibility firms may be more capital-intensive and exposed to greater cyclical operating risk despite possessing larger tangible asset bases.

At the same time, low-tangibility firms are both larger and slightly older on average, with a mean log total assets value of 9.317 compared to 9.056 and a mean log firm age of 4.435 compared to 4.320 among high-tangibility firms. This means that lower tangibility within the manufacturing sample does not necessarily correspond to younger or less established firms.

Redeployability differs only modestly across the groups despite strong statistical significance, meaning that raw tangibility and asset redeployability may capture different dimensions of collateral quality.

Overall, the descriptive statistics support three preliminary conclusions. First, the sample appears suitable for studying market-implied credit risk among large listed firms in manufacturing-related sectors. Second, leverage, profitability, firm size, and CDS spreads behave in financially plausible ways. Third, the descriptive evidence already implies that identifying a clean collateral-quality effect may be empirically difficult, particularly within the redeployability extension. These patterns guide the interpretation of the regression results that follow.

## **5. Empirical findings**

This section presents and interprets the empirical findings of the thesis. The analysis follows the logic of the research question and examines whether asset tangibility weakens the positive association between leverage and market-implied financial distress risk. Particular attention is given to the interaction between leverage and tangibility, since this coefficient is central to the hypothesis that collateral capacity moderates the pricing of leverage risk.

The section first presents the main panel-regression results using pooled OLS, firm fixed effects, and random effects specifications. The comparison across these estimators is important because the collateral channel may operate differently across cross-sectional and within-firm variation. The analysis then examines the redeployability extension as an exploratory test intended to distinguish between physical asset intensity and economically substantive collateral quality. Finally, several robustness tests are presented, including

Altman's Z-score, non-lagged explanatory variables, net leverage, and propensity-score matching within the high-leverage portion of the sample.

### **5.1 Baseline panel regressions and leverage-risk pricing**

Table 8 reports the main regression results. Column (1) reports pooled OLS estimates, Column (2) reports the preferred firm fixed-effects specification, Column (3) reports the random-effects model, and Column (4) reports an exploratory redeployability-adjusted specification intended to examine whether collateral-related dynamics become more visible when asset salability is incorporated into the tangibility measure.

The clearest result concerns leverage. Across all main CDS specifications, leverage remains positively associated with CDS spreads. In Column (1) of Table 8, the pooled OLS specification produces a leverage coefficient of 1.801, significant at the 1% level. In the preferred fixed-effects specification reported in Column (2), the coefficient declines to 0.486 but remains highly statistically significant. The random-effects estimate reported in Column (3) of Table 8 is likewise positive and highly significant at 0.991. Since the result appears consistently across specifications, it implies that credit markets price leverage as an important source of financial distress.

In the fixed-effects specification, an increase from 30 percent to 40 percent leverage is associated with roughly a 5% increase in CDS spreads. For a firm with the sample median CDS spread of approximately 88 basis points, this corresponds to an increase of approximately 4-5 basis points. This suggests that credit markets respond materially when firms become more debt-financed, even within the same firm over time. The findings are broadly consistent with trade-off theory and structural credit-risk models, where higher leverage increases expected distress costs and reduces the distance between firm value and promised debt payments (Myers, 1984; Merton, 1974).

This result aligns closely with economic intuition, as CDS spreads reflect the cost of default protection (Longstaff et al., 2005). When leverage increases, the claims on the firm's assets become larger relative to the asset base (Merton, 1974). Credit investors therefore require higher compensation. This relation remains visible even after controlling for firm fixed

effects, year effects, profitability, market valuation, and size. It means that the leverage result is not merely driven by permanently risky firms having higher debt. It also appears when firms become more levered over time.

The control variables generally behave as expected. Profitability is negative and statistically significant in the fixed-effects specification, indicating that firms with stronger operating performance tend to exhibit lower CDS spreads. Tobin's Q is likewise negative and significant. These findings indicate that credit markets place considerable weight on variables linked to debt-servicing capacity, refinancing pressure, and overall firm quality when pricing default protection. Firm size becomes statistically insignificant once firm fixed effects are introduced, which is plausible given that size differences are highly persistent across firms and hence largely absorbed by the fixed-effects transformation.

Overall, the baseline regressions provide strong support for H1. Higher leverage is robustly associated with higher market-implied financial distress risk. CDS markets therefore appear to price debt burden consistently and directly.

## **5.2 Tangibility, collateral capacity, and the weak interaction evidence**

The results for tangibility are considerably weaker than the results for leverage. No clear evidence emerges that tangibility by itself lowers CDS spreads. While tangible assets may improve expected recovery values in distress, firms with highly tangible asset bases also tend to operate with higher leverage (Rajan & Zingales, 1995). This pattern is already visible in the univariate comparison, where high-tangibility firms exhibit both higher leverage and higher CDS spreads on average. The direct tangibility coefficient should therefore not be interpreted as a clean test of the collateral effect.

The interaction between leverage and tangibility, which represents the central test of the thesis, is statistically insignificant in the preferred fixed-effects specification. The estimated coefficient is close to zero (0.023), providing limited evidence that accounting-based tangibility weakens the pricing of leverage-induced distress risk within firms over time.

This result makes a clear collateral-based interpretation of tangibility less convincing. If tangible assets directly reduced the credit-risk consequences of leverage, the interaction term would be expected to be negative and statistically significant. The fixed-effects evidence does not support such a conclusion. Although some benchmark specifications produce interaction

estimates in the expected direction, the preferred within-firm specification provides no statistically reliable evidence that increases in tangibility materially alter how CDS markets price leverage risk.

However, the insignificant interaction does not necessarily rule out collateral theory. Instead, book-based tangibility may simply be too crude to capture the specific recovery value priced by CDS investors. Shleifer and Vishny (1992) emphasize that liquidation value depends on whether assets can realistically be sold to financially unconstrained buyers in distress, not simply on whether assets are physically tangible. Campello and Giambona (2013) similarly argue that the salability of assets matters beyond conventional accounting tangibility measures, while Kim and Kung (2017) show that productive assets differ substantially in redeployability across uses and industries. Net PPE scaled by total assets may hence capture the quantity of tangible assets without adequately capturing pledgeability, secondary-market liquidity, asset specificity, or expected recovery value in distress.

Another possible explanation is that part of the collateral effect may already be embedded in observed leverage itself. Firms with stronger collateral capacity are generally able to borrow more and obtain financing on better terms because creditors recognize the presence of pledgeable assets (Almeida & Campello, 2007; Benmelech et al., 2005). In practice, leverage ratios may therefore already partly reflect underlying collateral conditions rather than representing a purely independent source of risk. Firms with stronger collateral positions are often able to sustain higher leverage precisely because creditors are more willing to lend against recoverable assets. Greater collateral capacity may therefore support additional borrowing rather than directly reducing market-priced distress risk. In this sense, the results appear more consistent with the debt-capacity channel emphasized in the capital-structure literature than with a simple interpretation in which tangible assets directly make leverage appear safer in CDS markets. If leverage already incorporates part of the information associated with collateral quality and borrowing capacity, it also becomes more difficult for the separate interaction term to capture an additional incremental collateral effect beyond leverage itself.

This pattern makes sense when looking at how CDS markets actually price risk. Even though a CDS spread should reflect both default probability and recovery value, the market under normal conditions reacts mostly to a firm's debt burden, profitability, and scale (Ericsson et al., 2009; Zhang et al., 2009). This explains why variables directly

linked to cash flows and leverage have a much stronger impact in our regressions than broad accounting measures of tangibility. In short, investors simply do not focus much on collateral until a firm gets close to actual distress.

This interpretation is particularly relevant given the composition of the sample. Much of the sample consists of relatively large and financially stable listed firms with persistent access to debt markets rather than firms operating near default. The average CDS spreads and Altman Z-scores indicate that most firms are not in immediate financial distress. As a result, CDS investors may place greater weight on firms' ability to service debt and maintain financing access than on liquidation-related recovery considerations during most firm-year observations.

The fixed-effects framework further strengthens this interpretation. Tangibility changes relatively slowly over time, particularly in manufacturing-related sectors where production structures and asset composition remain fairly stable. Firm fixed effects therefore absorb much of the persistent cross-sectional variation through which collateral capacity may realistically operate. This makes the collateral channel more difficult to detect empirically. The insignificant interaction term does not imply that collateral value is irrelevant. Instead, it suggests that annual adjustments in accounting-based tangibility do not materially alter how the CDS market prices firm-level leverage risk.

### **5.3 Cross-sectional versus within-firm evidence**

The comparison between pooled OLS, random effects, and fixed effects provides some of the most informative results in the thesis because the collateral dynamic may operate differently across cross-sectional and within-firm variation. Firms with highly tangible asset bases may differ systematically from less tangible firms in ways that extend beyond observable accounting ratios, including business models, asset specificity, refinancing conditions, operating cyclicity, and long-run risk characteristics. The contrast across estimators therefore contains valuable economic information rather than representing a purely technical robustness exercise.

The pooled OLS specification produces the largest leverage coefficient. In Column (1) of Table 8, the coefficient on leverage is 1.801 and highly statistically significant. Once firm fixed effects are introduced in Column (2), the coefficient declines materially to 0.486, although it remains statistically significant. The random-effects estimate reported in Column

(3) is likewise positive and highly significant at 0.991. This suggests that part of the pooled leverage effect is driven by persistent differences across firms rather than leverage changes alone.

The interaction term remains statistically insignificant across all specifications. While pooled OLS and random-effects models produce negative interaction estimates, the preferred fixed-effects specification produces an estimate close to zero and statistically insignificant.

The contrast across estimators may itself contain valuable economic information. One possibility is cross-sectional. Firms with more tangible asset bases may exhibit lower CDS spreads for a given level of leverage because creditors expect stronger recovery values in distress. At the same time, firms with high tangibility often differ from low-tangibility firms in several broader respects, including industry structure, refinancing conditions, cyclicalities, and long-run operating risk. Cross-sectional regressions may therefore capture more than the collateral effect alone (Lemmon et al., 2008).

CDS spreads may instead respond more strongly to variables that change more dynamically, such as leverage, profitability, refinancing conditions, and market-wide credit repricing. In this sense, leverage appears to function as a time-varying risk signal, while tangibility may operate more as a stable background characteristic embedded in long-run recovery expectations.

Taken together, the comparison across estimators supports two main conclusions. The first is that leverage is consistently priced as a source of distress risk in CDS markets. The second is more limited and nuanced. The evidence does not provide strong support for the view that annual changes in book-based tangibility materially alter how CDS markets price leverage risk within firms over time.

#### **5.4 Redeployability and the limits of collateral-quality measurement**

The redeployability extension was introduced to deal with one of the main weaknesses of raw tangibility measures. In distress, assets matter because they can be sold, transferred, pledged, or reused outside the current firm. A machine that only has value inside one production process is very different from an asset with an active secondary market and broader resale potential (Shleifer & Vishny, 1992).

Column (4) of Table 8 reports the redeployability-adjusted specification. The interaction between leverage and redeployability is negative and statistically significant, with a coefficient of -0.902. This provides some indication that more redeployable assets may weaken the positive relation between leverage and CDS spreads.

At the same time, the triple interaction between leverage, tangibility, and redeployability remains statistically insignificant despite a relatively large coefficient estimate of 10.120. The estimate is also imprecise, indicating substantial uncertainty around the interaction effect. The results therefore do not provide robust evidence that redeployability systematically strengthens the collateral link within the fixed-effects framework.

Part of the explanation likely comes from the structure of the sample itself. The thesis focuses on manufacturing-related sectors, where differences in redeployability across industries are relatively modest compared to a broader economy-wide sample. That naturally reduces variation in the redeployability measure. In addition, redeployability is assigned at the sector level and changes little over time, meaning that firm fixed effects absorb much of the remaining variation.

This creates a clear trade-off in the empirical design. Restricting the sample to manufacturing improves the theoretical fit of the analysis because tangibility is economically more meaningful in asset-intensive sectors than in industries dominated by software, platforms, or intangible capital. But the narrower sample also makes it harder to identify differences in collateral quality across firms and sectors.

The results for the redeployability extension reflect the inherent sector-level structure of the data rather than the absence of an underlying collateral channel. A stronger test would require more detailed information, such as asset-level redeployability, pledged collateral, debt seniority, recovery rates, or liquidation discounts. Data of that kind are difficult to obtain in large international panel settings. Even so, the results suggest that broad sector-level redeployability measures add limited explanatory power once firm fixed effects are introduced into the CDS framework.

Overall, the redeployability extension provides limited additional explanatory power beyond the baseline tangibility specification. More generally, the findings suggest that broad accounting-based collateral proxies may not fully capture the recovery-related information incorporated into CDS spreads.

## 5.5 Robustness checks

The robustness checks examine whether the baseline findings depend on the choice of distress measure, leverage definition, timing structure, or empirical design. The purpose is to evaluate whether the main interpretation remains stable across alternative specifications.

Across the robustness tests, the leverage effect remains relatively consistent. Where interaction effects are estimated, evidence for a moderating collateral effect remains limited.

### 5.5.1 Alternative distress measure: Altman Z-score

Table 9 reports the robustness specification using Altman's Z-score as the dependent variable instead of log CDS spreads. Unlike CDS spreads, where higher values indicate greater distress risk, higher Altman Z-scores indicate stronger financial health. The expected coefficient signs are therefore reversed relative to the baseline model.

The Altman specification is estimated using pooled OLS rather than firm fixed effects. This choice is motivated by the structure of the Z-score itself. Several components of the Altman measure display relatively limited within-firm variation over time, which makes fixed-effects estimation less suitable in this setting. Since the purpose of this robustness test is primarily to examine whether the broader leverage-distress relationship remains visible under an alternative distress proxy, pooled estimation is more appropriate in this setting.

The results remain broadly consistent with the baseline findings. Leverage is negative and statistically significant in Table 9, indicating that firms with higher leverage tend to exhibit lower Altman Z-scores and therefore weaker accounting-based financial health. Profitability and Tobin's Q are positively related to the Z-score, while firm size is negative and statistically significant.

The interaction term between leverage and tangibility is positive, which is consistent with the collateral hypothesis in a Z-score specification. However, the coefficient is statistically insignificant. Tangibility itself is also insignificant. The results therefore do not provide evidence that tangibility weakens the relationship between leverage and distress risk.

Overall, the Altman specification suggests that the leverage result is not limited to CDS-market pricing alone. Higher leverage is also associated with weaker accounting-based

financial health. At the same time, the absence of statistically significant interaction effects remains consistent with the main fixed-effects results.

### **5.5.2 Non-lagged specification**

Table 10 reports the fixed-effects specification without lagged explanatory variables. Instead of using one-year lagged accounting variables, the regression uses contemporaneous values. The purpose is to examine whether the baseline findings depend on the timing structure of the model.

The results remain broadly similar to the baseline specification. Leverage remains positive and statistically significant, while profitability, Tobin's Q, and firm size continue to display negative and statistically significant coefficients. Tangibility becomes negative and weakly significant in the non-lagged model.

The interaction term between leverage and tangibility remains statistically insignificant. As a result, the specification does not provide robust evidence that tangibility moderates the effect of leverage on CDS spreads.

At the same time, the non-lagged model introduces greater simultaneity concerns. CDS spreads and accounting variables may be jointly determined within the same period, particularly during periods of rapidly changing market conditions. The lagged baseline specification therefore remains preferable because it imposes a clearer temporal ordering between accounting information and subsequent CDS pricing.

Overall, Table 10 suggests that the main leverage result is not driven solely by the lag structure. However, the continued insignificance of the interaction term reinforces the broader conclusion that support for the collateral-moderation hypothesis remains limited.

### **5.5.3 Net leverage**

Table 11 reports the net leverage robustness specification. Gross leverage is replaced with net leverage, defined as total debt minus cash divided by total assets. This adjustment accounts for the fact that firms with substantial cash holdings may face lower effective debt burdens despite similar gross leverage ratios.

The results remain close to the baseline fixed-effects specification. Net leverage is positive and statistically significant in Table 11, indicating that firms with higher effective debt burdens tend to exhibit higher CDS spreads even after accounting for cash holdings. This implies that CDS markets price debt-related distress risk beyond mechanical differences in gross borrowing levels.

Tangibility remains statistically insignificant in the net leverage specification. The results therefore continue to provide limited support for the argument that collateral capacity weakens the relationship between leverage and distress risk.

Overall, the net leverage specification strengthens the interpretation that leverage itself is robustly associated with higher distress risk across alternative measurement choices.

#### **5.5.4 Propensity-score matching**

Table 12 reports the propensity-score matching (PSM) results, while Table 13 reports the corresponding balance diagnostics. The purpose of the matching analysis is to examine whether firms with high tangibility exhibit different CDS spreads than otherwise comparable firms with lower tangibility after controlling for observable firm characteristics.

The matching analysis is implemented within the high-leverage portion of the sample, defined as firms with leverage ratios above the sample median. This design follows the idea that collateral-related characteristics may become more relevant when leverage is high and financial distress risk becomes economically more salient. At relatively low leverage levels, creditors may place less weight on collateral value because default risk remains comparatively remote. As leverage increases, however, expected recovery values may become increasingly essential for credit pricing.

The matching procedure uses one-to-one nearest-neighbor propensity-score matching with common support. Within the high-leverage sample, firms with high tangibility are matched to otherwise comparable firms with lower tangibility using lagged firm characteristics.

Before matching, high-tangibility firms exhibit higher average CDS spreads than low-tangibility firms. As reported in Table 12, the unmatched difference in log CDS spreads is positive and statistically significant. After matching, however, the estimated average treatment effect on the treated (ATT) becomes negative and statistically significant.

High-tangibility firms in the matched sample exhibit lower average CDS spreads than comparable low-tangibility firms.

The unmatched comparison implies that high-tangibility firms are associated with higher CDS spreads, which is difficult to interpret as a direct collateral effect. After matching on observable firm characteristics, the relation becomes negative. This suggests that the raw positive association between tangibility and CDS spreads may partly reflect structural risk characteristics of asset-heavy firms rather than collateral capacity itself. Once high-tangibility firms are compared with more similar low-tangibility firms in the high-leverage portion of the sample, the evidence becomes more consistent with the idea that collateral-related characteristics may matter for recovery expectations.

The balance statistics reported in Table 13 indicate that the matching procedure substantially improves covariate balance between the treatment and control groups. The pseudo  $R^2$  declines from 0.026 to 0.001, while the mean bias falls from 17.3 to 2.2. In addition, the post-matching LR test becomes statistically insignificant, suggesting that observable differences between groups are largely eliminated after matching.

The PSM results provide some cross-sectional support for the idea that higher tangibility may be associated with lower market-implied distress risk when leverage is already high. This is consistent with the interpretation that collateral-related characteristics become more relevant when debt burdens make recovery expectations more salient for credit pricing. While these findings provide valuable insights, they are subject to the usual limitations of propensity-score matching. Specifically, the matching framework controls exclusively for observable characteristics and cannot fully account for unobserved heterogeneity. Furthermore, this cross-sectional approach inherently differs from the preferred fixed-effects specification, which relies on within-firm variation over time rather than comparisons across firms.

Overall, the matching analysis provides supplementary evidence that tangibility matters under certain settings, particularly among highly levered firms. However, the main fixed-effects regressions continue to provide limited evidence of a statistically robust collateral-moderating effect within firms over time.

## 5.6 What CDS markets appear to price

The results suggest that CDS markets appear substantially more responsive to debt burden and operating performance than to broad accounting-based measures of collateral capacity. Leverage remains consistently associated with higher CDS spreads, while profitability and Tobin's Q are negatively related to market-implied distress risk. Together, these findings indicate that credit markets place considerable weight on variables linked to debt-servicing capacity, refinancing pressure, and overall firm quality when pricing default protection.

That interpretation also makes economic sense. CDS spreads reflect both default probability and expected recovery, but the pricing contribution of default probability may dominate during normal credit conditions. Variables directly linked to debt burden and operating performance may therefore exert stronger effects on CDS spreads than broad accounting-based tangibility measures. Tangibility instead relates more closely to downside recovery in distress states, which may become financially essential only when default risk becomes sufficiently salient.

This interpretation aligns with the high-leverage matching analysis, which provides valuable complementary support for the main findings. Collateral-related characteristics appear more relevant among firms with greater debt burdens, where recovery expectations plausibly matter more for credit pricing. In the full fixed-effects specification, however, any collateral-related effect may become diluted across firms with relatively moderate levels of distress risk.

The findings therefore refine existing interpretations of collateral theory rather than contradict them. Traditional capital-structure research often treats tangibility as a determinant of debt capacity, but the results implies that greater borrowing capacity does not automatically translate into lower market-priced distress risk. CDS markets appear substantially more responsive to leverage itself than to annual changes in broad accounting-based tangibility measures.

For researchers, the thesis points to the need for better collateral measures. Sector-level redeployability is a useful conceptual improvement, but it remains limited in a manufacturing-only fixed-effects setting. More granular measures of collateral value would likely provide a stronger test of the theory. Future studies should distinguish more carefully between asset intensity and asset recoverability.

## **5.7 Limitations of the empirical findings**

As with any empirical analysis, the findings are subject to certain boundaries that shape their scope.

The empirical design does not establish causality. Leverage, tangibility, profitability, and CDS spreads are jointly determined, and firms may adjust capital structures in anticipation of changing credit conditions. CDS spreads may likewise respond to information that is not captured by accounting variables. Although lagged regressors and fixed effects reduce some simultaneity concerns, they do not fully eliminate endogeneity.

The composition of the sample also limits external validity. The analysis focuses on listed firms within manufacturing-related sectors with observable CDS data, meaning that the sample is concentrated among larger and more debt-market-visible firms. The findings should therefore primarily be interpreted as evidence for firms with active CDS-market pricing rather than for smaller private firms or firms without traded credit instruments.

An additional limitation follows from the sample construction itself. Firms are retained only if CDS observations remain available at the end of the sample period, which may underrepresent firms that disappeared from CDS markets due to delisting, restructuring, severe distress, or declining market activity before 2024. This may be particularly important for the collateral effect examined in the thesis. Firms experiencing severe financial distress may also be less likely to remain continuously observable in CDS markets, implying that the sample could underrepresent periods in which recovery values and collateral quality become particularly economically relevant. The weak interaction effect may therefore reflect the pricing of leverage risk primarily among firms with relatively stable CDS-market access rather than among firms facing acute distress or restructuring conditions.

The interaction framework itself is also statistically demanding. The leverage-tangibility interaction is by definition related to its underlying variables, while tangibility changes relatively slowly over time, particularly within manufacturing-related sectors where production structures remain fairly stable. Limited within-firm variation increases standard errors and makes moderation effects more difficult to identify within a fixed-effects setting. Consequently, the insignificant interaction indicates that while collateral capacity matters, its impact may operate through channels not fully captured by this specific measure.

Institutional heterogeneity further complicates the interpretation of the results. Although the international sample improves external breadth and increases the number of observable CDS firms, it also introduces substantial differences in bankruptcy regimes, creditor protection, collateral enforcement, accounting practices, and debt-market structures across countries. Recovery values are shaped not only by the physical nature of assets, but also by legal enforcement, restructuring procedures, creditor seniority, and the liquidity of secondary asset markets. Similar tangible asset bases may therefore provide very different levels of effective creditor protection depending on the surrounding institutional environment. Cross-country variation may consequently weaken the ability of broad accounting-based tangibility measures to capture market-perceived recovery value consistently across firms.

At the same time, the international setting also constitutes a strength. Since the findings are not driven by a single country-specific credit market or legal regime, the strong leverage effect observed in the thesis appears relatively robust across different institutional environments.

## **5.8 Summary of empirical findings**

Overall, the empirical findings provide strong support for the first hypothesis. Across both the preferred fixed-effects specification and the benchmark models, leverage remains positively and significantly associated with CDS spreads. Firms with higher leverage consistently exhibit higher market-implied distress risk. The result aligns closely with both trade-off theory and structural credit-risk models, where greater debt intensity increases expected distress costs and reduces the distance between firm value and promised debt payments.

The evidence for the second hypothesis is weaker. Although some benchmark specifications produce negative interaction estimates, the preferred fixed-effects specification provides no statistically significant evidence that tangibility weakens the pricing of leverage risk within firms over time. In practice, CDS markets appear to respond more directly to leverage itself than to the accounting composition of the asset base behind it.

The redeployability extension provides only limited support for the collateral-quality framework. Part of the explanation is methodological. Redeployability varies relatively little within the sample, leaving limited within-firm variation once fixed effects are introduced. That makes the liquidation-value channel difficult to within the preferred specification.

The robustness analyses nevertheless support the broader interpretation of the results. Leverage remains economically vital when net leverage is used and when financial distress is measured using Altman's Z-score, where higher leverage is associated with lower Z-scores and therefore greater accounting-based distress risk. The interaction effect however remains weak across the alternative specifications.

The high-leverage matching analysis points more in favor of the collateral hypothesis. Firms with stronger collateral-related characteristics appear to exhibit lower CDS spreads within the highly levered subsample after observable firm differences are reduced through matching.

Overall, the findings suggest that leverage is consistently priced as a source of financial distress risk in CDS markets, while the evidence that accounting-based tangibility alters that pricing remains limited within the present empirical framework.

## **6. Conclusion**

This thesis examined whether asset tangibility weakens the positive association between leverage and market-implied financial distress risk. Using CDS spreads and panel data from publicly listed firms in manufacturing-related sectors between 2015 and 2024, the analysis explored whether firms with more tangible asset bases appear less risky to credit markets when leverage increases.

The main finding is clear. Across both the preferred fixed-effects specification and the benchmark models, leverage remains positively and significantly associated with CDS spreads. Firms with higher leverage consistently exhibit higher market-implied distress risk. Credit markets therefore appear to price debt burden directly and consistently as a source of financial distress risk.

The findings for tangibility are less clear. Although some benchmark specifications produce negative interaction estimates, the preferred fixed-effects specification provides no statistically significant evidence that tangibility weakens the pricing of leverage risk within firms over time. A firm may be able to sustain more borrowing because it owns more tangible assets. That does not automatically mean that credit markets view the firm as safer once

leverage increases. This distinction between borrowing capacity and market-priced distress risk appears central to interpreting the results.

Part of the explanation likely lies in the distinction between borrowing capacity and market-priced recovery protection. Tangible assets may support higher debt capacity, but the results suggest that broad accounting-based tangibility does not necessarily make additional leverage appear materially safer in CDS markets. Credit markets likely respond to dimensions of collateral quality that are not fully captured by accounting ratios alone (Campello & Giambona, 2013). Consequently, debt capacity and debt safety should not automatically be treated as the same thing: tangible assets may support borrowing capacity, but the evidence does not show that they robustly reduce the market pricing of leverage-induced distress risk. Across the main specifications, CDS investors respond much more directly to leverage itself than to the accounting-based measure of the assets behind it.

Naturally, these results should be viewed within the scope of the empirical design. Tangibility and redeployability remain imperfect proxies for collateral quality, particularly in CDS markets where investors incorporate information extending beyond balance-sheet composition alone. In addition, the fixed-effects framework absorbs much of the persistent cross-sectional variation through which collateral dynamics may realistically operate.

The sample is also limited to firms with observable CDS-market pricing, which narrows the external validity of the findings. Future research could extend the analysis by incorporating asset-level recovery data, debt-contract information, recovery-rate measures, or market-based indicators of asset volatility. Such approaches would allow for a more direct test of whether collateral quality changes how credit markets price leverage risk.

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## 8. Appendix

**Table 1: Main Regression Sample**

|                        | Mean    | Median | SD      | Min    | Max    | N    |
|------------------------|---------|--------|---------|--------|--------|------|
| CDS spread (ln)        | 4.589   | 4.477  | 0.901   | 2.804  | 6.791  | 4738 |
| CDS spread (bps)       | 149.917 | 87.955 | 158.397 | 16.509 | 889.62 | 4738 |
| Leverage (t-1)         | .348    | .333   | 0.158   | .018   | .847   | 4738 |
| Tangibility (t-1)      | .305    | .263   | 0.208   | .009   | .849   | 4738 |
| Profitability (t-1)    | .082    | .073   | 0.064   | -.077  | .301   | 4738 |
| Tobin's Q (t-1)        | 1.456   | 1.098  | 1.039   | .35    | 5.612  | 4738 |
| Total assets log (t-1) | 9.186   | 9.126  | 1.212   | 6.147  | 12.334 | 4738 |
| Redeployability        | .408    | .415   | 0.022   | .373   | .443   | 4738 |
| Firm age log (t-1)     | 4.377   | 4.564  | 0.687   | 2.079  | 5.704  | 4738 |
| Firm age (t-1)         | 96.82   | 96     | 55.150  | 8      | 300    | 4738 |
| Altman Z-score         | 4.062   | 3.278  | 3.466   | .067   | 30.005 | 4052 |

**Table 2: Comparison of high and low tangibility sample**

| Variable               | Low Tangibility | High Tangibility | Difference | t-statistic |
|------------------------|-----------------|------------------|------------|-------------|
| CDS spread (ln)        | 4.530           | 4.647            | -0.117***  | -4.45       |
| Leverage (t-1)         | 0.335           | 0.362            | -0.028***  | -5.95       |
| Total assets log (t-1) | 9.317           | 9.056            | 0.261***   | 7.45        |
| Profitability (t-1)    | 0.086           | 0.079            | 0.007***   | 4.15        |
| Tobin's Q (t-1)        | 1.551           | 1.357            | 0.194***   | 6.45        |
| Firm age log (t-1)     | 4.435           | 4.320            | 0.116***   | 5.80        |
| Altman Z-score         | 4.458           | 3.650            | 0.808***   | 7.45        |
| Redeployability        | 0.414           | 0.403            | 0.011***   | 17.25       |

**Notes:** Difference is calculated as low tangibility minus high tangibility firms. Mean differences are tested using two-sided t-tests. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table 3: Sample Distribution by Geographic Region**

| <b>Geography</b>            | <b>Firms</b> | <b>Firm-years</b> | <b>Percent</b> |
|-----------------------------|--------------|-------------------|----------------|
| United States and Canada    | 322          | 2448              | 51.67%         |
| Asia-Pacific                | 288          | 1086              | 22.92%         |
| Europe                      | 187          | 986               | 20.81%         |
| Latin America and Caribbean | 31           | 195               | 4.12%          |
| Middle East                 | 3            | 14                | 0.30%          |
| Africa                      | 1            | 9                 | 0.19%          |
| <b>Total</b>                | <b>832</b>   | <b>4738</b>       | <b>100.00%</b> |

**Table 4: Sample Distribution by Industry Sector**

| <b>Industry</b>        | <b>Firms</b> | <b>Firm-years</b> | <b>Percent</b> |
|------------------------|--------------|-------------------|----------------|
| Industrials            | 320          | 1730              | 36.51%         |
| Consumer Discretionary | 222          | 1287              | 27.16%         |
| Materials              | 167          | 966               | 20.39%         |
| Consumer Staples       | 123          | 755               | 15.93%         |
| <b>Total</b>           | <b>832</b>   | <b>4738</b>       | <b>100.00%</b> |

**Table 5: Pairwise correlations**

| Variables                  | (1)           | (2)           | (3)           | (4)           | (5)          | (6)          | (7)          | (8)       | (9)       |
|----------------------------|---------------|---------------|---------------|---------------|--------------|--------------|--------------|-----------|-----------|
| (1) CDS spread (ln)        | 1.000         |               |               |               |              |              |              |           |           |
| (2) Leverage (t-1)         | 0.285**<br>*  | 1.000         |               |               |              |              |              |           |           |
| (3) Tangibility (t-1)      | 0.093**<br>*  | 0.133**<br>*  | 1.000         |               |              |              |              |           |           |
| (4) Profitability (t-1)    | -0.168**<br>* | 0.088**<br>*  | -0.093**<br>* | 1.000         |              |              |              |           |           |
| (5) Tobin's Q (t-1)        | -0.197**<br>* | 0.242**<br>*  | -0.088**<br>* | 0.618**<br>*  | 1.000        |              |              |           |           |
| (6) Total assets log (t-1) | -0.420**<br>* | -0.134**<br>* | -0.096**<br>* | -0.086**<br>* | 0.004        | 1.000        |              |           |           |
| (7) Redeployability        | -0.215**<br>* | 0.028*<br>*   | -0.243**<br>* | 0.061**<br>*  | 0.141**<br>* | 0.136**<br>* | 1.000        |           |           |
| (8) Firm age log (t-1)     | -0.124**<br>* | -0.068**<br>* | -0.109**<br>* | -0.007        | -0.018       | 0.084**<br>* | 0.018        | 1.00<br>0 |           |
| (9) Altman Z-score         | -0.318**<br>* | -0.332**<br>* | -0.152**<br>* | 0.427**<br>*  | 0.561**<br>* | 0.065**<br>* | 0.129**<br>* | 0.00<br>3 | 1.00<br>0 |

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

**Table 6 : Construction of Sector-Level Redeployability Measures Based on Kim and Kung (2017)**

| <b>GICS Sector</b>     | <b>Underlying Manufacturing Industries</b>                                                                                                                                                                         | <b>Number of Industries</b> | <b>Sector Redeployability</b> |
|------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------|-------------------------------|
| Industrials            | Printing & related support; Boiler, tank & shipping container; Cutlery & handtools; Ordnance & accessories; Other transportation equipment; Aerospace products & parts; Industrial machinery                       | 7                           | 0.4150                        |
| Materials              | Agricultural chemicals; Paint, coatings & adhesives; Other chemical products; Basic chemicals; Plastics & rubber; Pulp, paper & paperboard; Wood products; Converted paper products; Foundries; Iron & steel mills | 10                          | 0.3726                        |
| Consumer Discretionary | Leather & allied products; Household appliances; Apparel; Furniture & related products                                                                                                                             | 4                           | 0.4050                        |
| Consumer Staples       | Soap, cleaning compounds & toiletries; Tobacco                                                                                                                                                                     | 2                           | 0.4425                        |

**Notes:**

This table reports the construction of sector-level redeployability measures used in the redeployability extension of the thesis. The underlying manufacturing-industry redeployability measures originate from Kim and Kung (2017), who construct industry-level asset redeployability indices based on the extent to which productive assets can be reused across firms and industries

Because the empirical sample in this thesis is organized using broader GICS sector classifications, the original manufacturing-industry redeployability values are mapped into the corresponding GICS sectors. Sector-level redeployability measures are calculated as averages of the underlying manufacturing-industry redeployability scores associated with each sector.

**Table 7: White's test, Modified Wald test, Hausman test & VIF test**

| Test                          | Statistic                 | p-value | Interpretation                                                                                                                               |
|-------------------------------|---------------------------|---------|----------------------------------------------------------------------------------------------------------------------------------------------|
| White's test                  | $\chi^2(116) = 622.69$    | 0.0000  | Evidence of heteroskedasticity in residuals.                                                                                                 |
| Modified Wald test (FE model) | $\chi^2(832) = 431865.83$ | 0.0000  | Evidence of groupwise heteroskedasticity across panels.                                                                                      |
| Hausman test (FE vs RE)       | $\chi^2(15) = 342.37$     | 0.0000  | Reject RE assumption; FE preferred.                                                                                                          |
| Mean VIF                      | 2.91                      | -       | No evidence of severe overall multicollinearity                                                                                              |
| Highest VIF                   | 9.69                      | -       | Elevated primarily due to interaction-term construction. Mean VIF levels nevertheless indicate that multicollinearity is not severe overall. |

**Table 8: Regression Results**

|                          | (1)<br>POLS          | (2)<br>FE (Main)     | (3)<br>RE            | (4)<br>FE+Redeployability |
|--------------------------|----------------------|----------------------|----------------------|---------------------------|
| Leverage (t-1)           | 1.801***<br>(0.260)  | 0.486***<br>(0.185)  | 0.991***<br>(0.175)  | 0.830***<br>(0.194)       |
| Tangibility (t-1)        | 0.225<br>(0.275)     | -0.220<br>(0.251)    | -0.112<br>(0.197)    | -0.240<br>(0.245)         |
| Lev x Tang (t-1)         | -0.806<br>(0.669)    | 0.023<br>(0.514)     | -0.355<br>(0.481)    | -3.970<br>(3.300)         |
| Profitability (t-1)      | -1.169***<br>(0.440) | -1.058***<br>(0.199) | -0.809***<br>(0.195) | -1.049***<br>(0.199)      |
| Tobin's Q (t-1)          | -0.215***<br>(0.030) | -0.070***<br>(0.018) | -0.106***<br>(0.016) | -0.069***<br>(0.018)      |
| Total assets log (t-1)   | -0.287***<br>(0.020) | -0.060*<br>(0.033)   | -0.211***<br>(0.019) | -0.064*<br>(0.034)        |
| Firm age log (t-1)       | -0.095***<br>(0.032) |                      | -0.152***<br>(0.035) |                           |
| Redeployability          |                      |                      |                      |                           |
| Lev x Redep (t-1)        |                      |                      |                      | -0.902**<br>(0.351)       |
| Tang x Redep (t-1)       |                      |                      |                      | -0.141<br>(0.458)         |
| Lev x Tang X Redep (t-1) |                      |                      |                      | 10.120<br>(8.196)         |
| Observations             | 4738                 | 4738                 | 4738                 | 4738                      |
| R-squared                | 0.372                | 0.186                | .z                   | 0.187                     |
| Adj R <sup>2</sup>       | 0.370                | 0.184                | .z                   | 0.184                     |
| Method                   | POLS                 | FE                   | RE                   | FE                        |
| Year controls            | Yes                  | Yes                  | Yes                  | Yes                       |
| Industry controls        | No                   | No                   | No                   | No                        |

*Standard errors are in parentheses*

\*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$

*Firm age is omitted in the fixed-effects specifications due to collinearity with firm and year fixed effects. (Redeployability is largely time-invariant at the firm or sector level and is therefore absorbed by firm fixed effects in some specifications. The interaction terms nevertheless remain identifiable because they vary with time-varying firm characteristics such as leverage and tangibility)*

**Table 9: Altman's Z-score Robustness**

|                        | (1)<br>Altman         |
|------------------------|-----------------------|
| Leverage (t-1)         | -12.763***<br>(1.438) |
| Tangibility (t-1)      | -1.404<br>(1.612)     |
| Lev x Tang (t-1)       | 2.139<br>(3.832)      |
| Profitability (t-1)    | 4.231***<br>(1.557)   |
| Tobin's Q (t-1)        | 2.180***<br>(0.139)   |
| Total assets log (t-1) | -0.181***<br>(0.062)  |
| Firm age log (t-1)     | -0.019<br>(0.091)     |
| Observations           | 4837                  |
| R-squared              | 0.512                 |
| Adj R <sup>2</sup>     | 0.510                 |
| Method                 | POLS                  |
| Year controls          | Yes                   |
| Industry controls      | No                    |

*Standard errors are in parentheses*

\*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$

**Table 10: FE without lag Robustness**

|                    | (1)<br>R1_No_Lag     |
|--------------------|----------------------|
| Leverage           | 0.537***<br>(0.199)  |
| Tangibility        | -0.557*<br>(0.297)   |
| Lev x Tang         | 0.329<br>(0.570)     |
| Profitability      | -1.260***<br>(0.221) |
| Tobin's Q          | -0.110***<br>(0.019) |
| Total assets (log) | -0.129***<br>(0.043) |
| Observations       | 4681                 |
| R-squared          | 0.154                |
| Adj R <sup>2</sup> | 0.152                |
| Method             | FE                   |
| Year controls      | Yes                  |
| Lag                | None                 |

*Standard errors are in parentheses*

\*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$

**Table 11: FE with Net Leverage Robustness**

|                        | (1)<br>R2_Net_Leverage |
|------------------------|------------------------|
| Net leverage (t-1)     | 0.326***<br>(0.095)    |
| Tangibility (t-1)      | -0.252<br>(0.169)      |
| Profitability (t-1)    | -1.160***<br>(0.205)   |
| Tobin's Q (t-1)        | -0.066***<br>(0.018)   |
| Total assets log (t-1) | -0.063*<br>(0.033)     |
| Observations           | 4738                   |
| R-squared              | 0.183                  |
| Adj R <sup>2</sup>     | 0.181                  |
| Method                 | FE                     |
| Year controls          | Yes                    |
| Leverage               | Net                    |

*Standard errors are in parentheses*

\*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$

**Table 12: PSM Results**

| Outcome              | Treated | Control | Difference | t-statistic |
|----------------------|---------|---------|------------|-------------|
| ln(CDS), unmatched   | 4.647   | 4.531   | 0.117***   | 4.47        |
| ln(CDS), matched ATT | 4.647   | 4.757   | -0.110***  | -3.09       |

**Notes:** ATT denotes the average treatment effect on the treated. High tangibility firms are matched to low tangibility firms using one-to-one nearest-neighbor propensity-score matching with common support. \*\*\*  $p < 0.01$ .

**Table 13: Covariate Balance Before and After Matching**

| Statistic    | Before Matching | After Matching |
|--------------|-----------------|----------------|
| Pseudo $R^2$ | 0.026           | 0.001          |
| LR $\chi^2$  | 168.04          | 3.82           |
| p-value      | 0.000           | 0.576          |
| Mean bias    | 17.3            | 2.2            |
| Median bias  | 17.3            | 1.9            |

**Notes:** Balance statistics are based on propensity-score matching using lagged firm characteristics. Lower bias and pseudo  $R^2$  values after matching indicate improved covariate balance between treatment and control groups.

## 9. AI Statement

ChatGPT (OpenAI) was used to a limited extent for feedback on wording, spelling and practical guidance related to Stata syntax. All research design, methodological decisions, empirical analysis, interpretation of results, and conclusions were carried out by the authors. No confidential or proprietary data was shared with ChatGPT.