SCHOOL OF
ECONOMICS AND
MANAGEMENT

Hedged from the Edge

Evidence on hedging and default risk for U.S. nonfinancial firms

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Abstract

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Key words: Corporate hedging, Distance to default, Default risk, Credit default swaps, Bond yield spreads.

Purpose: This paper investigates whether derivative hedging is associated with lower default risk for U.S. firms, and whether this association differs when disaggregating the hedging by categories. It also examines the moderating effects of the firm's underlying exposure and agency problems.

Methodology: This study utilizes a hedging dataset constructed through automated textual extraction from 10-K filings in Python. The primary dependent variable is Merton's (1974) distance to default. The regressions are estimated using pooled OLS and firm fixed effects estimation, with year, and industry fixed effects when applicable. Standard errors are clustered at the firm level. Further, it employs lagged variable models, two propensity score matching approaches, and an instrumental variable in a 2SLS model.

Theoretical perspectives: The study's theoretical perspectives are financial distress costs, financing frictions, agency conflicts, and information asymmetry.

Empirical foundation: The empirical foundation follows a panel of nonfinancial Russell 3000 firms from 2014 to 2024. Financial controls and market-based credit risk measures are from Bloomberg, Capital IQ Pro, and FactSet. The sample covers 3,757 unique firms, yielding 21,508 firm-year observations.

Conclusions: The findings of this study differ from those of earlier studies. It finds weak but significant evidence of a lower default risk from the aggregate decision to hedge. The strongest effect on the reduction in default risk is observed from the commodity hedging indicator, which is robust across several specifications. It also finds support that the negative effects from agency conflicts are positively moderated by the aggregate hedging decision.

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1. Introduction

This chapter establishes why corporate hedging matters from a risk management perspective. It describes the study's motivation by identifying a gap in the literature on hedging and default risk, and presents the research questions, main findings, contributions, and an outline of the paper.

1.1 Background

Between 2022 and 2023, the Federal Reserve raised the effective funds rate from near zero to above five percent, the fastest tightening cycle in decades (Federal Reserve Bank of St. Louis, 2025). Corporate borrowing costs surged, and investment-grade credit spreads widened (Schwab, 2025). Firms that had locked in low rates through fixed-rate debt contracts or derivative hedging strategies were strategically better positioned than those with unhedged exposures. Periods like these illustrate a point that risk management theories have made for a long time: managing cash flow volatility affects the firm's ability to survive (Smith & Stulz, 1985; Stulz, 1996).

The global over-the-counter derivatives market reached $846 trillion in notional amount outstanding by mid-2025, the largest year-on-year increase since before the 2008 financial crisis (Bank for International Settlements, 2025). Although this figure is not limited to nonfinancial firms, it illustrates that corporations increasingly seek protection against market fluctuations. The majority of nonfinancial firms in the United States use interest rate (IR), foreign exchange (FX), or commodity derivatives, and risk management is seen as one of the most important responsibilities of the corporate treasury function (Giambona et al. 2018).

Despite the scale at which firms hedge, empirical research has largely studied the relationship between risk management and firm value (Allayannis & Weston, 2001; Fauver & Naranjo, 2010; Geyer-Klingeberg et al. 2021). However, firm value is arguably a second-order effect of hedging benefits (Gilje & Taillard, 2017). Theoretical models predict that hedging primarily reduces cash flow volatility, lowers expected distress costs, and relaxes financing constraints (Froot et al. 1993; Smith & Stulz, 1985). From this perspective, a more direct implication of hedging could be reduced default risk, with the firm's value-enhancing effect following. This study therefore shifts the focus from firm value to default risk and, more specifically, investigates the relationship between corporate hedging and distance to default.

1.2 Problem Discussion

The most direct predecessor to this paper is Magee (2013), who studied a U.S. sample and found that the extent of FX hedging is linked to a lower probability of default, measured by Merton's (1974) distance to default. Judge et al. (2026) recently extended this analysis to European nonfinancial firms. They showed that derivative use lowers Moody's expected default probabilities, with interest rate derivatives having the largest effect. Related literature examines whether hedging affects debt pricing rather than the probability of default. Chen and King (2014) provide evidence that hedging firms have a lower cost of debt, measured by bond yield spreads. Campello, Lin, Ma, and Zou (2011) show that hedging relaxes financing constraints on loans through lower interest spreads and fewer restrictions on capital expenditure.

Against this background the study has two main motivations. First, the existing default risk and hedging research for the U.S. sample by Magee (2013) ends in 2000 and is limited to a single derivative category (FX). The European evidence by Judge et al. (2026) is recent and comparable, but the sample ends in 2015 and uses a different default measurement. This study measures default risk using the Merton (1974) distance to default, which is available for a large share of U.S. firms. We complement this with credit default swap (CDS) spreads and option-adjusted bond yield spreads (OAS) as market-implied robustness measures for subsamples where they are available. Second, we hypothesize that underlying firm exposure, agency costs, and derivative risk category affect the effectiveness of hedging in reducing default risk, and we construct models to test this.

1.3 Purpose and Research questions

The purpose of this study is to investigate whether corporate hedging reduces default risk for U.S. nonfinancial firms. We use the Merton (1974) distance to default as the primary measure, complemented by CDS and OAS spreads for subsamples to capture market perceptions of credit risk. The paper is motivated by the comparatively thin coverage in previous U.S. work and the lack of recent evidence on the relationship between hedging and distance to default. We address the following research questions:

1. *Is corporate hedging through derivatives associated with a lower default risk, measured by Merton's (1974) distance to default?*

2. *Does the default risk effect of hedging vary across categories of financial risk (FX, IR, and Commodity)?*

3. *Do underlying exposures and agency frictions change the impact of hedging on default risk?*

1.4 Main Findings

The results suggest that commodity hedging is the most robust predictor of a higher distance to default and remains statistically significant across pooled OLS, firm fixed effects, lagged specifications, and propensity score matching. The economic magnitude of commodity hedging on distance to default is 3.1% of the sample mean in the multivariate baseline model. Foreign exchange hedging is associated with a higher distance to default in pooled OLS and propensity score matching, but the effect is absorbed under firm fixed effects. Interest rate hedging yields the weakest results among the three categories. It is significant only under propensity score matching, in contrast to Judge et al. (2026), that finds the strongest effect for IR derivatives among European firms.

The aggregate decision to hedge is only weakly associated with a higher distance to default in pooled OLS and firm fixed effects regressions. The economic magnitude of the aggregate effect is small, representing approximately 1.2% of the sample mean distance to default. Finally, we observe that the negative effects from agency costs on distance to default is positively moderated by the aggregate decision to hedge.

1.5 Contributions

This study contributes to the literature of corporate risk management in four ways. First, it examines the relationship between corporate hedging and default risk in a new time setting and for a wider sample of firms. Prior studies end before the pandemic and do not capture recent macroeconomic conditions (Magee, 2013; Judge et al. 2026; Chen & King, 2014). Second, it extends Magee (2013) by using distance to default in a larger sample and by measuring two additional hedging risk categories. Third, it addresses robustness by complementing distance to default with both CDS spreads and bond yield spreads, allowing us to assess whether the results generalize. Fourth, it employs large-scale automated hedging text extraction from 10-K filings, enabling a comprehensive binary hedging dataset across the Russell 3000. This results in a studied sample of 21,508 firm-year observations, in contrast to the smaller or hand-collected samples used in prior research (Chen & King, 2014; Campello et al. 2011; Magee, 2013).

1.6 Outline of the Paper

The remainder of the paper is structured as follows. Chapter 2 reviews the theoretical and empirical literature on corporate hedging and default risk to derive testable hypotheses. Chapter 3 describes the data sources, sample-selection process, and variable construction. Chapter 4 presents the econometric methodology, including the baseline panel specification, the propensity-score matching procedure, and the interaction tests. Chapter 5 reports the empirical results, including robustness checks. Chapter 6 discusses the findings in relation to theory and prior literature, and Chapter 7 concludes.

2. Literature review

This chapter presents the theoretical background explaining why corporate hedging can be value-increasing when capital markets are imperfect. It then reviews empirical evidence on hedging and its impact on default risk, firm value, and cost of debt. The chapter concludes by deriving hypotheses grounded in the literature.

2.1 Theoretical Background

2.1.1 Modigliani & Miller and the Capital Market Imperfections

The foundation of modern corporate finance begins with Modigliani and Miller's (1958) world without frictions. Under their assumption of perfect capital markets, a firm's financial policy, including risk management, is irrelevant to its value. In this ideal setting, characterized by the absence of transaction costs, taxes, and bankruptcy costs, firm value is solely determined by expected return from its underlying assets. Under the Modigliani and Miller (1958) assumptions, corporate hedging will not change firm value since shareholders can replicate or undo any of the firm's risk-reduction decisions through their own diversified portfolios. The subsequent theoretical literature explains why hedging becomes relevant when relaxing these perfect capital market assumptions, highlighting the costs of financial distress (Smith & Stulz, 1985), financing frictions (Froot et al. 1993), agency costs (Myers, 1977; Jensen & Meckling, 1976), and information asymmetry (DeMarzo & Duffie, 1995) as central frictions.

2.1.2 Financial Distress Costs

Financial distress is a firm condition between the states of being solvent and insolvent, where worsening cash flows and losses do not yet result in legal bankruptcy (Purnanandam, 2008). While bankruptcy itself occurs when a firm is unable to pay its debt obligations (Jensen & Meckling, 1976), financial distress often refers to the preceding period of significant financial difficulty (Purnanandam, 2008). In an imperfect capital market, the expected costs relating to financial distress can significantly reduce a firm's value (Smith & Stulz, 1985). These costs fall into two main categories: direct costs, such as legal and administrative fees, and indirect costs, such as loss of key personnel and tougher terms from suppliers (Bris et al. 2006; Purnanandam, 2008; Stulz, 1996).

Smith and Stulz (1985) and Stulz (1996) argue that corporate hedging creates value by decreasing the likelihood of lower-tail, worst case scenarios that can trigger distress for a firm, thereby reducing its expected financial distress costs. By smoothing cash flows, hedging strengthens the firm's ability to meet its debt payments. A reduction in cash flow volatility can, in turn, lower firm asset volatility, which within the Merton (1974) model increases the distance to default. Further, a lower probability of default can translate into better financing terms, including lower interest spreads on loans and lower required yields on bonds (Campello et al. 2011; Chen & King, 2014).

2.1.3 Investment and Financing Frictions

Froot, Scharfstein, and Stein (1993) provide another value increasing theory for hedging, based on the capital market imperfection that external financing is more costly than internal. When external financing is expensive, firms with insufficient internal cash might be forced to forego positive net present value projects. By reducing the variability of internally generated funds, hedging ensures that investment decisions are less sensitive to cash-flow shocks and reduces the expected cost of financing constraints or credit rationing. For a levered firm, protecting internal funds could be associated with a lower probability of default since it allows for sufficient debt service capabilities and undertaking NPV-positive investments (Froot et al. 1993).

2.1.4 Agency Conflicts

Two agency conflicts between shareholders and creditors are central to how hedging affects credit risk. First, Myers (1977) identifies the underinvestment problem and argues that shareholders of firms with risky debt may forgo positive-NPV projects if gains are primarily distributed to bondholders. Bessembinder (1991) argues that hedging mitigates this problem by lowering the firm's risk and leaving equityholders with more upside from new projects and a greater incentive to invest. Further, by committing the firm to meet its debt obligations in adverse states, hedging both increases the value of creditor claims and benefits shareholders, which are residual claimants in default states (Bessembinder, 1991).

Second, Jensen and Meckling (1976) identify the risk-shifting or asset-substitution problem, where shareholders of a financially distressed firm are incentivized to invest in high-risk, negative-NPV projects because they capture the upside while debtholders bear the downside risk. Campbell and Kracaw (1990) demonstrate that hedging commitments mitigates the risk-shifting problem. Through stabilizing the firm's asset base, hedging limits opportunities for such risk-shifting. Both conflicts predict that hedging should reduce the agency cost of debt, and creditors should therefore demand lower yields and assess a lower probability of default.

The theoretical literature also considers how ownership structure can shape a firm's propensity to hedge (Smith & Stulz, 1985; Stulz, 1984). Well-diversified shareholders can reduce diversifiable risk within their portfolios, making corporate hedging largely irrelevant. Risk management only adds value when it addresses market frictions, such as the expected costs of financial distress (Stulz, 1996). However, when the transaction costs of implementing a hedging program outweigh the friction-based benefits, firm-level hedging can fail to increase or even destroy value for these shareholders (Smith & Stulz, 1985). In contrast to shareholders, managers often cannot diversify their human capital or wealth tied to the firm, leading them to use hedging to mitigate the firm-specific risks that they personally bear (Smith & Stulz, 1985). This problem is similar in nature to the free cash flow problem proposed by Jensen (1986) in which managers will act in their self interest if they are allowed to and induce agency cost.

2.1.5 Information Asymmetry and Signaling

DeMarzo and Duffie (1995) and Breeden and Viswanathan (1998) argue that hedging allows managers to reduce information asymmetry and better communicate firm quality by filtering out earnings noise and therefore display firm quality. If firm cash flows are largely driven by uncontrollable external factors, such as changes in exchange rates or commodity prices, risk management can remove a layer of noise, making performance a cleaner signal of managerial ability and firm fundamentals (Breeden & Viswanathan, 1998). In turn, this allows managers to separate themselves, where high-ability managers are more likely to hedge than low-ability ones. DeMarzo and Duffie (1995) additionally explain that hedging incentives are impacted by the accounting disclosure environment. If hedge transactions are disclosed separately, investors can in principle undo the hedge, weakening the signaling content. If aggregate earnings are reported instead, investors cannot distinguish the operating performance from hedging gains or losses. This can arguably lead managers to hedge more to stabilize reported earnings, and shareholders may prefer limited disclosure, as it encourages greater risk reduction and smoother earnings (DeMarzo & Duffie, 1995).

2.2 Empirical Literature

2.2.1 Hedging and Firm Value

The empirical literature on hedging largely consists of firm value studies with conflicting results. In a large sample of U.S. firms, the seminal paper by Allayannis and Weston (2001) documented that foreign currency hedgers enjoy approximately 5% higher value premium than non-hedgers. However, Jin and Jorion (2006) find no evidence of a hedging premium in the U.S. oil and gas industry, where commodity exposures are measurable, and hedging is directly observable. Gilje and Taillard (2017) use an exogenous change in basis risk within the U.S. oil and gas sector to provide causal evidence that hedging affects firm value. They illustrate that firms experiencing a reduction in hedging effectiveness invested less, sold more assets, and obtained lower market valuations. Their findings are concentrated among highly leveraged firms. Furthermore, Fauver and Naranjo (2010) show a hedging value discount in firms with high agency and monitoring costs, consistent with the mechanism from Smith and Stulz (1985) that managerial self-interest can drive hedging decisions at the expense of shareholders.

The meta-analysis of Geyer-Klingeberg, Hang, and Rathgeber (2021) connects decades of empirical evidence and reaches two conclusions which help shape this study. First, the hedging premium differs across risk categories. Foreign exchange hedgers earn the largest average premium of 1.8% while interest rate and commodity hedgers show value discounts of -0.8% and -0.6%, respectively. Second, they highlight that reported premiums are highly sensitive to study design, finding that excluding firm fixed effects and endogeneity controls creates an upward bias in estimated value effects.

2.2.2 Hedging and Cost of Debt

Evidence from credit markets, where hedging is examined through the pricing effects on debt instruments, is relevant to this study, since the cost of debt reflects market assessments of a firm's default risk. Chen and King (2014) studied a large U.S. nonfinancial sample from 1994 to 2009 and used corporate bond yield spreads as a proxy for the cost of debt. They find that, on average, hedgers exhibit yield spreads nearly 50 basis points lower than non-hedgers. The hedging and yield-reducing effect is twice as large for speculative-grade issuers, which is consistent with financial distress concerns. To address potential endogeneity, they employ propensity score matching, which shows that firms initiating (suspending) experience a drop (jump) in the cost of debt. Chen and King (2014) also find support for the agency cost and information asymmetry through interaction tests.

Campello et al. (2011) provide evidence at the loan level. In a sample of U.S. nonfinancial firms over 1996-2002, they show that hedging firms face lower interest spreads and fewer investment restrictions on their loans than non-hedgers. Through easing access to credit and lowering borrowing costs, hedging allowed firms to increase their investment spending by approximately 13% compared to the sample mean. Their findings support the financing friction of Froot et al. (1993), in which hedging protects internal cash flows and mitigates the underinvestment problem from costly external financing.

2.2.3 Hedging and Default Risk

The literature on hedging and default risk remains small compared with the firm value studies. The most direct predecessor of this study is Magee (2013), who focuses exclusively on FX hedging. Following a sample of 401 large U.S. nonfinancial firms from 1996 to 2000, the study finds a significant correlation between the extent of FX hedging and a higher Merton (1974) distance to default. Magee (2013) also documents that a simple binary decision to hedge yields insignificant results, which suggests that the magnitude rather than the mere presence of hedging activity drives the effect on default risk. To address endogeneity concerns, Magee employs an instrumental variable approach to find that failing to account for the simultaneous hedging and leverage decisions underestimates the benefits of hedging. The results provide empirical support for Smith and Stulz's (1985) hypothesis that derivatives increase firm value by reducing expected costs of financial distress.

Building on a similar foundation, Judge et al. (2026) examine how derivative use impacts default probability among European nonfinancial firms. They utilize Moody's estimated default frequencies (EDFs), which are based on Merton's (1974) distance to default model. They find evidence that users of derivatives have a 13-20% lower risk of default than non-users. Further, derivatives appear to be more effective in reducing near-term default risk than in mitigating longer-term default probabilities. A key distinction in their results is that interest rate derivatives showed a stronger effect in reducing default risk than foreign exchange or commodity derivatives. Judge et al. (2026) explain it as a firm's interest rate management and capacity to serve debt having a closer link.

For nonfinancial S&P 500 firms over 2003-2011, Anbil, Saretto, and Tookes (2019) measure how derivative use under hedge accounting rules impacts the market's perception of credit risk. They find that firms with derivative positions not designated as accounting hedges, which typically carry higher basis risk, have higher CDS spreads than firms with designated hedges or no derivatives at all. This effect was not found due to derivative speculation. Instead, they show that periods of macroeconomic uncertainty cause the observed effect. In this study, CDS spreads are used as a robustness measure, providing a market-based, forward-looking variable that directly prices firms' default risk.

2.3 Hypothesis Development

The theoretical and empirical literature reviewed above combine to suggest that corporate risk management mitigates default risk. Theories regarding the financial distress costs (Smith & Stulz, 1985), financing frictions (Froot et al. 1993), and agency conflicts (Bessembinder, 1991; Campbell & Kracaw, 1990) all predict that hedging should reduce default risk through smoother cash flows. Empirically, Magee (2013) finds that the extent of FX hedging is linked to a higher distance to default, while Judge et al. (2026) document that derivative users have a 13% to 20% lower probability of default. Furthermore, Chen & King (2014) show lower bond yield spreads for hedging firms, and Campello et al. (2011) document lower loan spreads. Since Merton (1974) distance to default is a forward-looking measurement based on market values (Magee, 2013), under the Efficient Market Hypothesis (Fama, 1970), hedging benefits should be reflected in the firm, where a higher distance to default means a lower default risk. We therefore hypothesize:

H1*: Corporate hedging is associated with a higher distance to default.*

The meta-analysis of Geyer-Klingeberg et al. (2021) shows that firm value effects of hedging differ across hedge types. Foreign exchange hedging yields value premiums on average, while interest rate and commodity hedging were associated with value discounts. Similarly, Judge et al. (2026) document a varied pattern in default risk, with interest rate hedging showing a more pronounced reduction in default probability than FX or commodity derivatives. We accordingly hypothesize that hedging is associated with a higher distance to default within each derivative category, while remaining open regarding the relative ranking across them:

H2a: *Foreign exchange hedging is associated with a higher distance to default*
H2b*: Interest rate hedging is associated with a higher distance to default.*
H2c*: Commodity hedging is associated with a higher distance to default.*

In addition to the main hypotheses, we develop sub-hypotheses in an attempt to capture the moderating effects of firm exposure and agency costs. For foreign exchange exposure, Allayannis and Weston (2001) document that their hedging premium is concentrated among U.S. firms with foreign sales. Additionally, Allayannis and Ofek (2001) show that U.S. firms with greater foreign sales hedge more intensively with currency derivatives. Since foreign revenues expose firms to currency fluctuations that can increase cash flow volatility, FX hedging is expected to stabilize cash flows and lower default risk more for firms with greater exposure. Following this logic, we hypothesize:

H3*: The positive association between FX hedging and the distance to default is stronger for firms with a higher foreign sales ratio.*

For interest rate exposure, firms with higher interest coverage ratios should be better equipped to meet their debt obligations and less likely to default. For these firms, the benefit of risk management may be lower because their risk of default is already minimal (Chen & King, 2014). On the other hand, firms that exhibit weak coverage face higher financial risk, and their hedging benefits should be relatively higher since they are more sensitive to interest rate fluctuations (Ahmed et al. 2018; Chen & King, 2014). Judge et al. (2026) argue that interest rate hedging is crucial for the capacity to service debt since it manages the payments that can trigger a default. Chen and King (2014) show that a decrease in the cost of debt is greater for hedgers with low interest coverage. We expect a similar pattern for default risk, and thus, we hypothesize:

H4*: The positive association between interest rate hedging and distance to default is stronger for firms with low interest coverage ratios.*

For commodity exposure, manufacturing firms are frequently subject to commodity price fluctuations because production inputs such as energy, metals, and raw materials are purchased at market-determined prices. Anbil et al. (2019) document that industry-level input intensity affects firm-level risk. When these inputs exhibit price volatility, the firm's operating margin is impacted, and in turn, the volatility of the firm's cash flows increases. Anbil et al. (2019) mention that commodity hedging involves large basis risk due to imperfect contract alignment, but risk management can still be a vital tool for cost stability for manufacturing firms. Chen and King (2014) show that credit markets reward this by reducing the cost of debt for commodity hedging firms with such exposure. Again, we expect a similar pattern for default risk, and thus, we hypothesize:

H5*: The positive association between commodity hedging and distance to default is stronger for firms in commodity-intensive industries.*

Finally, among the classical market frictions outlined in Section 2.1, agency conflicts can be tested in line with the literature. Fauver and Naranjo (2010) document that hedging firms with high agency conflicts between managers and shareholders, proxied as free cash flow to assets, exhibit a negative association with firm value. If hedging can mitigate agency conflicts, as argued by Bessembinder (1991) and Campbell and Kracaw (1990), a hedging firm with high agency costs should be less likely to default compared to a non-hedger. In line with this theory, we hypothesize:

H6: *The positive association between hedging and the distance to default is stronger for firms with higher agency costs.*

3. Data and Descriptive Statistics

This chapter describes the sample selection process, the Merton (1974) distance to default, the binary hedging indicators from 10-K filings, and the construction of the control and moderating variables. Lastly, it shows the descriptive statistics and pairwise correlations.

3.1 Sample Selection

The initial sample universe contains all firms included in the Russell 3000 equity index as of the last trading day of each observation year from 2014 to 2024, yielding 32,206 firm-year observations. The Russell 3000 captures approximately 98% of the investable U.S. equity market by market capitalization (FTSE Russell, 2024). It should therefore provide substantial variation in firm size, industry, and exposure to interest rate, currency, and commodity price fluctuations. The 2014-2024 period covers a range of macroeconomic developments, including the pandemic shock, the subsequent inflation surge, and the 2022-2023 monetary tightening cycle.

The following filters are applied to the initial sample: (1) exclude financial firms (SIC 6000-6999) and regulated utilities (SIC 4900-4999), following standard practice in the hedging literature (Magee, 2013; Chen & King, 2014; Campello et al. 2011; Fauver & Naranjo, 2010), because these sectors face specific risk management regulation and accounting treatment; (2) require a 10-K filing available on SEC EDGAR for each firm-year observation; (3) require sufficient accounting and market data on S&P Capital IQ Pro to construct variables, and (4) for the CDS spread and bond yield subsample, we require five-year mid CDS spreads to be available on Capital IQ Pro and the bond option-adjusted spread to be available on Bloomberg for at least one year of the sample period. All continuous accounting and ratio variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers, in line with Judge et al. (2026). After applying the filters, the final main sample comprises 21,508 firm-year observations, covering 3,757 unique firms. A detailed industry composition of the sample is reported in Table 2.

3.2 Dependent Variable: Distance to Default

The dependent variable is the Merton (1974) distance to default (DD), calculated following the procedures of Campello et al. (2011) and Magee (2013). DD measures the number of standard deviations the market value of a firm's assets lies above the default threshold over the one-year horizon. DD increases with a firm's asset-to-debt ratio, since a larger asset stake implies a wider buffer above the default threshold. DD also increases with expected return on assets since a more profitable firm moves further from default, considering any given level of leverage and volatility. Importantly, DD decreases with asset volatility, since higher volatility increases the probability of default. The inference from the variable is therefore that a higher DD is associated with a lower probability of default. The distance to default takes the following form, where all inputs are taken at each firm's fiscal year-end:

$$Distance\ to\ default_t = \frac{ln\,(V_t/F) + (\mu - \frac{1}{2}\sigma_V^2)\,T}{\sigma_V\sqrt{T}}$$

where V_t is the market value of the firm's assets, F is the default threshold (defined as debt in current liabilities plus one-half of long-term debt), μ is the expected return on assets (set equal to the risk-free rate r), σ_V is the asset volatility, and T is the time horizon, set to one year (Magee, 2013).

Because the market value of assets (V_t) and asset volatility (σ_V) are not directly observable, they are inferred by solving two nonlinear equations simultaneously (Campello et al. 2011; Magee 2013). The first is the Black-Scholes-Merton equation, which treats the market value of equity as a European call option on the firm's assets. Under the Black-Scholes (1973) assumptions, the value of the firm's equity is written as:

$$E_t = V_t N(d_1) \ - \ Fe^{-rT}N(d_2),$$

$$\text{with } d_1 = \frac{ln(V_t/F) + (r + \frac{1}{2}\sigma^2 V)T}{\sigma_V\sqrt{T}}, \text{ and } \quad d_2 = d_1 - \sigma_V\sqrt{T}$$

where r is the risk-free rate proxied by the 3-month U.S. treasury bill rate, and N is the standard normal cumulative distribution function. The second equation relates the observable equity volatility (σ_E) to the unobservable asset volatility (σ_V):

$$\sigma_E = \frac{V_t}{E_t} N(d_1)\sigma_V$$

where E_t is the market value of equity (fiscal year-end market capitalization), and σ_E is the one-year equity volatility (estimated from daily stock returns over the preceding fiscal year).

Following Magee (2013), the equations are solved numerically to reach a unique value for V_t and σ_V for each firm-year observation.

DD is available for any publicly traded firm with sufficient equity-return history and observable leverage. It therefore provides broader coverage of the Russell 3000 than the robustness measures in Section 3.3, and is successfully generated for 16,205 firm-year observations. Although the Merton (1974) model relies on simplifying assumptions, it is considered a strong predictor of default and widely used in default risk research (Bharath & Shumway, 2008; Jessen & Lando, 2015). Discussion on the shortcomings of DD can be seen in Section 6.4.

3.3 Alternative Default Risk Measurements

3.3.1 Credit Default Swap Spread

Following the methodology of Anbil et al. (2019), we utilize the natural logarithm of the five-year mid conventional credit default swap (CDS) spread as the main robustness measure and proxy for default risk. It is a market-based variable, and the five-year tenor is liquid and widely quoted (IHS Markit, 2021). The variable is retrieved from Capital IQ Pro at each firm's fiscal year-end during the sample period, resulting in 5,431 firm-year observations. We apply a logarithmic transformation to address skewness in the spread distribution, consistent with standard practice in the credit-risk literature (Anbil et al. 2019; Bharath & Shumway, 2008). Importantly, a higher CDS spread indicates greater market-implied credit risk, the opposite direction of DD.

3.3.2 Bond Yield Spreads

For firms with publicly traded bonds, we retrieve the bid option-adjusted spread (OAS) from Bloomberg for all outstanding bonds as of each firm's fiscal year-end. In the fixed income screener, the following filters were used as of the last NYSE trading day of each observation year from 2014 to 2024: (1) active bonds; (2) denominated in U.S. dollars; (3) amount outstanding greater than 0; (4) excluding perpetual bonds; (5) excluding securitized bonds. Since we want one observation per firm-year, we calculate the weighted average OAS spread using the amount outstanding as the weight, similar to Chen and King (2014). Using the U.S. dollar denomination avoids currency conversion, and the bid option-adjusted spread is chosen over ask or mid quotes due to data availability. The variable was collected for 4,281 firm-year observations. As with CDS, a higher OAS implies greater credit risk.

3.4 Hedging Indicators

Hedging indicators are constructed through automated text classification of 10-K filings. For each firm-year, the annual 10-K filing is retrieved from the SEC's EDGAR database and analyzed to identify mentions of derivative instruments and hedging activity. We construct three binary indicators that take the value 1 if the firm uses derivatives to hedge foreign exchange, interest rate, and commodity risk, and 0 otherwise. We also construct an aggregate hedging indicator that takes the value 1 if the firm uses any derivative for hedging purposes and 0 otherwise. A firm can be classified as a hedger across multiple categories simultaneously. The detailed description of the textual extraction process is provided in Appendix H and includes a breakdown of our manual auditing process.

The binary hedging indicators rely on the U.S. derivative disclosure requirements throughout the 2014-2024 sample period. During this time, U.S. firms were governed by ASC 815 (formerly SFAS 133) (KPMG, 2026). While the ASU 2017-12 regulation became effective for fiscal years beginning after 2018, the fundamental requirements for providing comprehensive qualitative and quantitative derivative disclosure remained a consistent feature of U.S. GAAP (KPMG, 2026). Although a detailed analysis of hedge accounting disclosure is outside the primary scope of this study, noting these regulatory standards is essential because the research model relies on data extracted from the 10-K filings subject to these requirements to accurately categorize the hedging dummies.

We initially attempted to extract notional hedging amounts from the 10-K filing to construct continuous hedging intensity measures used by Magee (2013) and Campello et al. (2011). Unfortunately, not all firms report notional amounts for hedging, and only about 1000 firm-year observations were collected (less than 5% of the collected binary hedging observations). An even larger problem was that the inconsistent reporting of this number led to faulty extraction. For example, the model had particular difficulty finding the correct notional number and scaling it to the correct unit, and it also double-counted when the same amount was mentioned twice. We therefore decided, after careful manual audit and troubleshooting, not to include notional amounts and hedging intensity in our sample, since the data could not be retrieved reliably, and instead focus on retrieving the more precise binary variables. This is further discussed in Section 6.4.

3.5 Control Variables

Following prior literature on credit risk and hedging (Magee, 2013; Chen & King, 2014; Campello et al., 2011; Anbil et al., 2019), we select a collection of control variables intended to absorb variation in default risk that is uncorrelated with hedging activity. The table below presents details on how the control variables are constructed, along with the motivation and the expected coefficient sign on DD. All accounting data are denominated in U.S. dollars and collected at each firm's fiscal year-end date.

Variable	Construction and motivation	Expected sign on DD
Size	Natural logarithm of total assets (Magee, 2013; Judge et al. 2026; Chen & King, 2014). Larger firms generally enjoy a more diversified product and asset base, better access to external capital, and a lower probability of default (Judge et al. 2026). Hence, we expect a higher distance to default. Geyer-Klingeberg et al. (2021) report that size is used in over 97% of hedging firm value models.	+
Profitability	EBITDA divided by total assets (Chen & King, 2014; Campello et al. 2011). It proxies the firm's ability to generate cash flow sufficient to service debt, and we expect, similar to Magee (2013), that its coefficient should be positive.	+
Leverage	Total liabilities divided by total assets (Magee, 2013; Chen & King, 2014; Campello et al. 2011). Leverage is the main driver of default risk because it reflects the claims that must be met to avoid bankruptcy. A higher levered firm is expected to have a higher probability of default.	-
Stock volatility	One-year annualized stock price volatility (Magee, 2013; Judge et al. (2026). Greater volatility implies more uncertainty regarding a firm's future asset value and cash flows. Equity volatility is a direct input to the Merton (1974) DD model and creates a mechanical relationship, as mentioned by Magee (2013), and therefore, a robustness test is done for this.	-
Cash holdings	Cash and short-term investments divided by total assets. (Magee, 2013; Chen & King, 2014; Campello et al. 2011). High liquidity acts as a buffer against financial distress and periods of low cash flows, increasing the distance to default.	+
Tobin's Q	Market capitalization plus total debt divided by total assets (Chen & King, 2014). Proxies growth opportunities and the market's valuation of the firm relative to the replacement cost of its assets. While high market value may increase risk due to agency problems, it also provides a financial cushion that may lower the risk (Chen & King, 2014). The expected effect on default risk is ambiguous.	+/-
Tangibility	Net property, plant, and equipment divided by total assets (Chen & King, 2014; Campello et al. 2011; Anbil et al. 2019). Tangible assets can serve as collateral, easing access to credit and improving financial health.	+

3.6 Moderating Variables

To test hypotheses H3 through H5, we construct firm-level measures of underlying exposure for each hedge type. For H3, FX exposure is measured as the ratio of foreign sales to total sales, following the approach of Allayannis and Weston (2001). This variable is interacted with the currency hedging dummy to capture the mitigating effect of derivatives on such exposure (Allayannis & Ofek, 2001). For H4, IR exposure is proxied by the interest coverage ratio, following Chen and King (2014), to measure vulnerability to interest rate fluctuations and it is interacted with the interest rate hedging dummy. For H5, commodity exposure is identified using an indicator variable for firms operating in commodity-intensive industries. Based on Purnanandam (2008), we specifically target mining, food production, chemicals, and petroleum refining (SIC 1000–1499, 2000–2099, 2800–2899, 2900–2999, respectively) as sectors with significant commodity risk. Finally, to test H6 regarding agency conflicts, we use the ratio of free cash flow to assets as a proxy for the monitoring environment and potential misalignment of interests between managers and shareholders, following Fauver and Naranjo (2010).

3.7 Summary Statistics and Correlations

Table 1 presents the winsorized summary statistics for the main variables used in the regression models, and raw variables are presented in Appendix L for transparency. The mean distance to default is 2.805 with a median of 2.617, indicating that the average firm is approximately 2.8 standard deviations away from its default barrier at the one-year horizon. The aggregate hedging indicator shows that 54.4% of firm-year observations utilize any derivative hedging. Across the three categories, 40.3% of observations hedge FX risk, 44.1% hedge IR risk, and 15.4% hedge commodity risk. The lower frequency of commodity hedging is expected, since commodity exposure is concentrated in a smaller subset of industries, reflecting a pattern similar to that documented by Judge et al. (2026) for European firms.

For the firm-level control variables, the average firm has total assets of $8.6 billion, liabilities-to-assets of 28.8%, EBITDA-to-assets of 3.8%, cash holdings of 16.6% of assets, and PP&E of 21.9% of assets. The average Tobin's Q is 2.303, and the average one-year stock return volatility is 46.62%. In panel C, our moderating variables are presented. The average firm has 25.82% of its revenue coming from foreign markets, an interest-coverage ratio of 19.153, and a free cash flow to assets ratio of -0.003. Furthermore, commodity-intensive sectors account for 12.1% of the firm-year observations.

Table 2 shows that the mean distance to default varies across the sample period, with a high of 3.574 recorded in 2017 and a low of 1.728 recorded in 2020. Variation also exists when firms are broken down by sector in the same table, with Panel B showing that Energy has the lowest distance to default and consumer staples the highest. The two alternative measures of default risk, CDS and OAS spreads, also vary across years and industries.

Table 3 presents pairwise correlations among the variables used in the baseline regression models, and the three default risk measures are in line with expectations. Distance to default is strongly negatively correlated with both logged CDS spreads and logged OAS spreads, with coefficients of -0.605 and -0.526, respectively. The strong positive correlation between logged CDS spreads and logged OAS spreads (0.790) supports the view that both spread-based variables reflect similar credit-risk information (Bharath & Shumway, 2008). Since a higher DD indicates lower default risk, while higher spreads indicate higher default risk, these negative correlations suggest that the three measures capture related but inversely scaled dimensions of credit risk.

The hedging variables show correlations consistent with H1 and H2. The aggregate hedging indicator is positively correlated with DD (0.192) and negatively correlated with both logged CDS spreads (-0.133) and logged OAS spreads (-0.097). Similar patterns are observed across the individual hedge categories. FX hedging has the strongest correlation with distance to default (0.276) and is also negatively correlated with CDS and OAS spreads. Interest rate hedging and commodity hedging show the same directional pattern, although the correlations are somewhat weaker.

The control variables generally display correlations in line with expectations. Leverage is negatively correlated with distance to default, while size, profitability, cash holdings, and tangibility are positively correlated. Stock-return volatility has a particularly strong negative correlation with distance to default (-0.848), which is taken into account and addressed further in Section 4.2.2. Stock-return volatility also shows a moderate correlation with CDS and OAS spreads, which is not unexpected, since its correlation with distance to default was also moderately high. Further, we note a correlation of 0.896 between free cash flow to assets and profitability, which is comparably high. The implications of this multicollinearity for our study are further discussed in Section 4.2.2.

4. Methodology

This chapter outlines the econometric framework used to test the hypotheses. It begins by describing the econometric method, including univariate tests, the multivariate specifications, and specifications for testing moderating hypotheses. We then present the modeling choices and multicollinearity diagnostics. Lastly, we discuss robustness measures, lagged specifications, propensity score matching and an instrumental-variable approach.

4.1 Econometric Methodology

We first perform a univariate test to identify mean differences between hedgers and non-hedgers, as standard practice in the literature (Chen & King, 2014; Campello et al. 2011; Magee, 2013). This is followed by multivariate tests for the primary hypotheses. The baseline models are estimated using Pooled Ordinary Least Squares (POLS) with industry and year fixed effects. In POLS, all firm-year observations are pooled over time, units, and groups, and the panel data setting is ignored (Wooldridge, 2016). This approach is widely used in prior corporate hedging literature as the main baseline model (Magee, 2013; Allayannis & Weston, 2001; Jin & Jorion, 2006; Anbil et al. 2019).

To account for concerns that observations within the same firm are likely correlated over time, we employ firm-clustered standard error, as recommended by Wooldridge (2016). This decision is further supported by the results from a white's test (Appendix B), which rejects the null of homoscedasticity, favoring clustered standard errors to manage heteroskedasticity in the models. This approach allows the error variance to vary across firms while also accounting for serial correlation within firms over time. As a result, the standard errors provide more reliable and conservative inference regarding the relationship between hedging and distance to default.

4.1.1 Univariate Tests

The paper's analysis begins with dividing the sample into hedgers and non-hedgers. We perform a univariate comparison of the means for our dependent, control, and moderating variables between the two groups. This approach allows us to determine whether there is a meaningful difference between the two groups in the observable characteristics. We utilize a two-sample t-test, as prior literature (Chen & King, 2014; Campello et al. 2011). We disaggregate the hedging group into specific risk categories, foreign exchange (FX), interest rate (IR), and commodity, as well as the aggregate hedging to analyze whether firms managing different types of risk show distinct characteristics compared to the non-hedger control group.

4.1.2 Multivariate Tests

To test our main hypotheses, H1 and H2a-c*,* we estimate three sets of multivariate models. Models (1) through (5) use Merton's (1974) distance to default (DD) as the dependent variable to proxy for market-perceived default risk. Model (1) uses a general hedging dummy as the primary explanatory variable, while models (2) through (4) introduce specific dummies for each risk category. Model (5) is our baseline specification, which includes all three hedging risk categories simultaneously to account for potential confounding effects from firms using multiple derivative types (Judge et al. 2026). The general baseline specification can therefore be presented for models (1) through (5):

$$DD_{i,t} = \beta_0 + \beta_1 Hedging_{i,t} + \beta_2 Controls_{i,t} + \delta_j + \lambda_t + \varepsilon_{i,t} \quad (1)—(5)$$

Where $DD_{i,t}$ is Merton's (1974) distance to default for firm i in year t, $Hedging_{i,t}$ is a binary indicator equal to one if the firm *i* uses derivatives in year *t* (overall, FX, IR, or commodity, depending on the specification). $Controls_{i,t}$ is the set of firm-level control variables: leverage, size (log total assets), profitability, cash holdings, tangibility, Tobin's Q, and stock-return volatility, described in Section 3.5. The firm-level controls stay the same throughout the specifications. To account for year and industry effects δ_j and λ_t denote industry (two-digit SIC) and year fixed effects, respectively, $\varepsilon_{i,t}$ is the composite error term and β_0 is the intercept.

Models (6) through (10) replace DD with the natural logarithm of the 5-year credit default swap spread (CDS) as the dependent variable, following Anbil et al. 2019. All other features from the baseline are retained. Since CDS data was only available for a portion of the Russell 3000, these models serve both as a subsample analysis and a robustness test using an alternative market-based risk indicator. The specification is:

$$ln(CDS)_{i,t} = \beta_0 + \beta_1 Hedging_{i,t} + \beta_2 Controls_{i,t} + \delta_j + \lambda_t + \varepsilon_{i,t} \quad (6)—(10)$$

Finally, Models (11) through (15) introduce the natural logarithm of the weighted average bond option-adjusted spread (OAS) as the dependent variable, following a similar approach as Chen and King (2014). Similarly, OAS data was only available for a portion of Russell 3000 firms since it required outstanding bonds. We retain all other features from the baseline specification, and it therefore follows the specification:

$$Ln(OAS)_{i,t} = \beta_0 + \beta_1 Hedging_{i,t} + \beta_2 Controls_{i,t} + \delta_j + \lambda_t + \varepsilon_{i,t} \qquad (11) — (15)$$

4.1.3 Multivariate Tests of Underlying Exposure and Frictions

To test our hypotheses H3 through H6, we extend our baseline models using interaction terms in four ways. First, we follow Allayannis and Ofek (2001) and interact the FX hedging dummy with the foreign sales to total sales ratio. The rationale is that firms with high foreign sales face greater exposure to currency fluctuations and therefore hedging should yield a larger reduction in default risk for these firms. Second, we introduce an interaction term between the IR hedging dummy and the interest coverage ratio, following Chen & King (2014), to assess whether hedging matters more in reducing default risk for firms with greater interest rate vulnerability. Third, we interact the commodity hedging dummy with an indicator for commodity-intensive sectors (Chen & King, 2014; Purnanadam, 2008) to assess whether the effect of hedging is stronger for firms in these high-exposure industries. The fourth alteration of the baseline models interacts our overall hedging dummy with the free cash flow-to-assets ratio, following Fauver and Naranjo (2010). Firms with a higher FCF-to-assets ratio may be more prone to agency conflicts, in which hedging could serve as a mechanism to mitigate the risk of value-destroying behavior by management (Fauver & Naranjo, 2010).

All three specifications retain the firm-level controls used in the baseline model (5). Results are estimated using POLS with industry and year fixed effects as the main specification. A robustness specification using firm fixed effects is also employed for each model, with motivations discussed further in Section 4.2.1. The general specification of models (16), (18), and (20) used to test H3 to H5 is therefore as follows:

$$DD_{i,t} = \beta_0 + \beta_1 Hedging_{i,t} + \beta_2 (Hedging \times Exposure) + \beta_3 Exposure_{i,t} + \beta_4 Controls_{i,t} + \delta_j + \lambda_t + \varepsilon_{i,t} \qquad (16)$$

$$Ln(CDS)_{i,t} = \beta_0 + \beta_1 Hedging_{i,t} + \beta_2 (Hedging \times Exposure) + \beta_3 Exposure_{i,t} + \beta_4 Controls_{i,t} + \delta_j + \lambda_t + \varepsilon_{i,t} \qquad (18)$$

$$Ln(OAS)_{i,t} = \beta_0 + \beta_1 Hedging_{i,t} + \beta_2 (Hedging \times Exposure) + \beta_3 Exposure_{i,t} + \beta_4 Controls_{i,t} + \delta_j + \lambda_t + \varepsilon_{i,t} \quad (20)$$

Where $Exposure$ is a general placeholder for the moderating variables used to test H3 through H5 (foreign revenue exposure, interest rate coverage, commodity-intensive sector), each model is run three times, once for each exposure variable. Models (17), (19), and (21) follow similar specifications to the models above but are estimated with firm fixed effects for robustness. For testing H6, the exposure variable is substituted by the FCF-to-assets ratio. H6 is therefore tested utilizing the following main specifications for models (22), (24), and (26):

$$DD_{i,t} = \beta_0 + \beta_1 Hedging_{i,t} + \beta_2 (Hedging \times \frac{FCF}{TA}) + \beta_3 \frac{FCF}{TA} + \beta_4 Controls_{i,t} + \delta_j + \lambda_t + \varepsilon_{i,t} \quad (22)$$

$$Ln(CDS)_{i,t} = \beta_0 + \beta_1 Hedging_{i,t} + \beta_2 (Hedging \times \frac{FCF}{TA}) + \beta_3 \frac{FCF}{TA} + \beta_4 Controls_{i,t} + \delta_j + \lambda_t + \varepsilon_{i,t} \quad (24)$$

$$Ln(OAS)_{i,t} = \beta_0 + \beta_1 Hedging_{i,t} + \beta_2 (Hedging \times \frac{FCF}{TA}) + \beta_3 \frac{FCF}{TA} + \beta_4 Controls_{i,t} + \delta_j + \lambda_t + \varepsilon_{i,t} \quad (26)$$

Models (23), (25), and (27) are constructed for robustness and follow a similar specification to the models presented above, but use firm fixed effects as the estimation method instead of POLS.

4.2 Modeling Choices

4.2.1 Fixed Effects Versus Random Effects

As mentioned, firm fixed effect (FE) estimation is used as a robustness check in several of our multivariate regression models, following previous literature (Campello et al., 2011; Chen & King, 2014). By utilizing FE, we can estimate the results after removing the time-invariant unobserved effects and factors such as managerial talent, thereby controlling for time-constant omitted variables that may be correlated with our regressors (Wooldridge, 2016). In contrast, the random effects (RE) estimator is considered more efficient, but it assumes that the unobserved effects are uncorrelated with the regressors, and a violation of this assumption yields inconsistent estimates (Wooldridge, 2016).

To justify our model selection, we perform a Hausman (1978) test to compare the FE and RE specifications. The results, reported in Appendix C, show a rejection of the null hypothesis and indicate that unobserved firm-level heterogeneity is correlated with the regressors, suggesting that FE is required to ensure consistent estimates (Wooldridge, 2016). Despite this result, we retain the POLS specification with industry and year fixed effects as the baseline and present firm fixed effects as a robustness check, following Chen and King (2014), and Anbil et al. (2019). We see value in using FE for robustness, as Geyer-Klingeberg et al. (2021) document that excluding FE inflates the reported coefficient sizes in their meta-analysis of firm value and hedging, making FE specification a strict test of the baseline result. We therefore report both specifications and interpret a result that holds under firm fixed effects as a stronger finding than one that holds only under POLS.

4.2.2 Multicollinearity Diagnostics

To ensure stability of our estimates, we test for multicollinearity using a VIF test on our baseline models presented in Appendix A. No variable exhibits a problematic VIF score since the highest is 3.6, which is below the common guideline of 10 (Bharath & Shumway, 2008). Our pairwise correlation matrix, presented in Table 3, reveals a correlation of -0.848 between stock volatility and distance to default. This correlation is high and expected since the variable is used in part to construct our distance to default measure. In line with Magee (2013), we perform robustness checks using lagged and excluded stock volatility to validate our findings. Results are presented in Appendix D and confirm that the inference remains robust to these modifications. Finally, to address the high correlation between profitability and FCF to assets, stemming from their shared operating performance metrics, we estimate a model excluding profitability (Appendix F), which supports that the results are not driven by this mechanical overlap.

4.3 Robustness

4.3.1 Endogeneity

For this study, a central econometric concern is that corporate hedging decisions are potentially endogenous. As noted by Roberts and Whited (2013), endogeneity arises when an explanatory variable is correlated with the regression error term, which may lead to biased and inconsistent estimates. In our setting, the potentially endogenous variable is the hedging indicator because firms do not randomly choose whether to hedge (Purnanandam, 2008). For instance, the decision to hedge can be determined together with capital structure (leverage), where highly levered firms are more likely to hedge, and hedging can simultaneously increase debt capacity (Chen & King, 2014; Purnanandam, 2008).

Reverse causality is another source of concern. Firms might increase derivative use when default risk rises, rather than hedging use leading to a lower default risk (Judge et al. 2026). For example, when a firm nears extreme financial distress, hedging incentives can reverse, as shareholders prefer risk-shifting to seek low probability but highly rewarding outcomes rather than hedging to reduce bankruptcy costs (Purnanandam, 2008). Omitted variable bias is an additional concern that may arise because hedging firms might differ from non-hedging firms in unobservable ways, such as managerial preference or risk culture (Roberts & Whited, 2013). These factors can affect default risk independently, thereby biasing the coefficients on hedging in either direction.

Finally, measurement error in the hedging classification is a concern because our binary variables capture the decision to hedge rather than the intensity of hedging. Additionally, the 10-K filing based extraction might be impacted by the reporting quality of hedges: larger firms with longer, more detailed disclosure about their hedging practices may receive a hedging classification more frequently than smaller firms with relatively shorter derivative disclosure. To address endogeneity concerns, we employ several robustness checks, including firm fixed effects (Section 4.2.1), lagged variable models (Section 4.3.2), two propensity score matching models (Section 4.3.3), and an instrumental-variable specification (Section 4.3.4). These methods do not fully eliminate endogeneity concerns, but they help assess whether the estimated relationship between hedging and default risk is robust to alternative empirical specifications.

4.3.2 Lagged Models

To enhance robustness towards our main specifications, we introduce two lagged-variable specifications that differ in how they lag the explanatory variables. The first specification, presented in Table 10 as Models (28) through (32), lags only the hedging dummies by one year ($t-1$) while retaining the firm controls at year t. The motivation is that hedging decisions may take time to materialize in observable cash flow stability and, in turn, in the firm's distance to default. Lagging the hedging variable allows us to observe whether previous-year hedging status is associated with current default risk, reducing concerns that the correlation between hedging and credit risk reflects reverse causality.

The second specification, Models (28a) through (32a), presented in Appendix G, extends this logic by lagging all explanatory variables, both the hedging indicators and the firm-level controls, while keeping the dependent variables at year t. The motivation behind this is the following: the distance to default is a forward-looking measure constructed from market values of equity and equity volatility (Magee, 2013), and should therefore be predictable from predetermined firm characteristics rather than from those reported in the same year. Following Chen and King (2014), we treat lagged controls as a way to mitigate simultaneity between our explanatory variables and market-perceived credit risk.

4.3.3 Propensity Score Matching

We employ propensity score matching (PSM), similar to Chen and King (2014), as a robustness measure for our baseline regression results. The propensity score is the predicted probability of hedging estimated from a logit model on the lagged (t-1) firm-level controls (Leverage, Size, Profitability, CashHoldings, Tangibility, Tobin's Q, StockVolatility) together with year dummies. Each treated firm-year is matched 1:1 to its nearest non-treated neighbor within a small caliper of 0.01 in propensity-score units.

We also employ another PSM model presented in Appendix E. To isolate the within-firm effect of changes in hedging behavior, we follow Chen and King (2014) and identify hedging initiation and suspension events for each of the four hedging dummies. An initiation event is a firm-year in which the hedging indicator equals 1 at year t and 0 at year t–1; a suspension event is the reverse. Firms may contribute multiple events over the sample period. Initiation events are matched to firm-years that are non-hedgers in both t–1 and t (stable non-hedgers); suspension events are matched to firm-years that are stable hedgers. This restriction on the comparison group ensures that controls have the same hedging status in both years, isolating the effect of the transition rather than the level of hedging. We chose this slightly more relaxed classification of initiation and suspension to capture more observations of change, compared with Chen and King (2014), who allowed the firm to change status only once and then remain with the same status to be included in their model.

For each event type and outcome, we estimate a propensity score using a logit model with lagged firm controls and year fixed effects. Treated and control observations are matched 1:1 to the nearest neighbor within a caliper of 0.01 in propensity-score units. We report the average treatment effect on the treated for the change in the outcome between t–1 and t, where the outcome is the three different default measures (Appendix E).

Following Roberts and Whited (2013), the purpose of the matching is not to establish causality, but to reduce observable differences between treated and control firms. PSM relies on the assumption of unconfoundedness, meaning that selection into hedging is based on observable characteristics, and overlap, meaning that comparable non-hedging firms exist for hedging firms. Since selection on unobservable factors may remain, the PSM results are interpreted as robustness evidence rather than definitive causal estimates.

4.3.4 Instrumental Variable

An instrumental variable approach is employed using two-stage least squares (2SLS) to address potential endogeneity in the hedging decision. The instrument is the lagged sector-year leave-one-out peer hedging rate, defined as the average hedging activity among other firms in the same sector in the previous year, following the approach used by Allayannis, Lel, and Miller (2012) and Bartram (2019). The intuition is that firms are more likely to hedge when hedging is common among sector peers, due to similar exposures, industry norms, and treasury practices. By excluding the firm itself and using the lagged value, we reduce concerns about mechanical correlation and simultaneity. The instrument is used in the Model (33) specification and shows signs of being a strong instrument, with an F score of 21.5, which exceeds the common threshold of 10 proposed by Staiger and Stock (1997).

The validity of the IV approach relies on two assumptions: relevance and exclusion (Roberts and Whited, 2013). Relevance requires the peer hedging rate to predict the firm's own hedging decision by being correlated with the variable. Exclusion requires that peer hedging affects the firm's default risk only through its effect on the firm's own hedging. As Roberts and Whited (2013) emphasize, this exclusion restriction cannot be directly tested and must therefore be justified economically. For example, while an industry peer's hedging policy can influence a firm's choice to hedge, it does not directly alter a firm's cash flow volatility or asset-liability structure. The central threat is that firms within the same sector are exposed to common shocks in interest rates, commodity prices, and exchange rates. If such a shock simultaneously raises peer hedging activity and alters the firm's default risk through the shared underlying exposure rather than through the firm's own hedging, the instrument affects the outcome through a channel other than the one assumed, and the exclusion restriction fails. As discussed in Section 5.4, the implausibly large second-stage coefficient is consistent with this concern and we therefore present the results from the 2SLS model for transparency but do not draw conclusions from it.

5. Empirical Results

This chapter presents the study's empirical results and evaluates them in relation to the hypotheses developed in Chapter 2. The analysis begins with a univariate analysis of hedgers and non-hedgers, followed by the baseline multivariate results for firms' distance to default, and then discusses moderating specifications and findings from robustness checks.

5.1 Univariate Results

Table 4 presents two-sample t-tests of mean differences between hedging and non-hedging firms across the three default risk measures, the firm-level controls, and the moderating variables. Panel A compares the simple aggregate hedge group to non-hedgers, while Panels B through D disaggregate by FX, IR, and commodity hedging. For the aggregate hedging indicator in Panel A, hedgers show a mean distance to default of 2.995 compared to 2.476 for non-hedgers, which equals approximately a 21% higher DD for hedgers. Hedgers also display lower CDS spreads and OAS spreads compared to non-hedgers. All three differences in means are statistically significant at the 1% level. Panels B through D illustrate the pattern for each category-specific hedging indicator, with FX hedgers showing the largest difference in distance to default. This univariate result is consistent with meta-analytical evidence on firm value, where FX hedging has the largest average premiums (Geyer-Klingeberg et al. 2021).

The univariate comparison shows that hedgers differ substantially from non-hedgers in terms of observable firm characteristics. In line with the literature, hedgers are larger, more profitable, and carry higher leverage (Campello et al. 2011). It also follows Jin and Jorion's (2006) suggestion that larger firms are more likely to use hedging because of economies of scale. Additionally, hedgers hold less cash and show a lower one-year stock volatility (Purnanadam, 2008; Judge et al. 2026). When disaggregating the three hedge categories in Panels B through D, the same pattern is shown. The univariate results present two main implications. Hedgers display lower default risk on all three measures, and hedgers also differ from non-hedgers on every observable firm characteristic. Since these characteristics themselves are determinants of default risk, the mean differences in default risk shown in Panel A are likely to be substantially overstated (Allayannis & Weston, 2001). We turn to multivariable analysis to isolate the partial effect of hedging after controlling for differences in firm characteristics.

5.2 Baseline Multivariate Results

5.2.1 Distance to Default

Table 5 reports the baseline regression results for the distance to default specifications. Panel A shows the pooled OLS estimates with industry and year fixed effects, while Panel B displays estimates with firm- and year fixed effects. All standard errors are clustered at the firm level.

Model (1) of Panel A introduces the aggregate hedging indicator (Hedgeoverall) alongside the firm-level controls. The coefficient is 0.034 and statistically significant at the 5% level, suggesting that hedging is associated with greater distance to default. We therefore accept H1. However, the economic magnitude is modest, since an increase of 0.034 in distance to default represents only 1.2% of the full sample mean of 2.805 reported in Table 1, and accounts for less than 7% in relation to the raw mean difference between hedgers and non-hedgers documented in Table 4. The remaining 93% of the univariate difference is hence absorbed by the control variables. This indicates the univariate comparison substantially overstated the conditional effect of hedging.

Models (2), (3), and (4) replace the aggregate hedging indicator with each category-specific dummy in isolation with control variables included. The interest rate, foreign exchange, and commodity hedging coefficients are positive and statistically significant. Commodity hedging shows the strongest single-category effect, raising distance to default by approximately 3.6% relative to the sample mean. Model (5) includes all three hedging categories simultaneously. The interest rate coefficient becomes statistically insignificant, the foreign exchange coefficient declines to 0.050 but remains statistically significant. The Commodity coefficient declines slightly to 0.087 which represents a positive economic effect equal to 3.1% of the sample mean DD, but it remains highly statistically significant. In line with these results, we accept hypotheses H2a and H2c but not H2b. This deviates from Judge et al. (2026), who find that interest rate derivatives show the strongest risk reduction.

In the firm fixed-effects specification in Panel B, the aggregate hedge coefficient declines slightly to 0.032 and is significant only at the 10% level. The category-specific effects are concentrated in commodity hedging, which retains statistical significance under the FE specification of Model (5) with a smaller coefficient of 0.044 ($p < 0.1$). FX and IR hedging are not significant in any of the firm fixed-effect specifications. The loss of significance for FX and IR hedging aligns with Geyer-Klingeberg et al. (2021) suggestion that studies excluding firm fixed effects models yield biased results. For the CDS and OAS spread subsamples, presented in Tables 6 and 7, respectively, the aggregate hedging variable and the category-specific variables are not statistically significant.

5.2.2 Interaction Results

In Table 8, results are presented after introducing interaction variables to test H3 through H6 on the moderating effects of firm-specific risk exposure and agency costs. Panel A displays the interaction between the FX hedging dummy and the foreign sales ratio. Consistent with baseline results, the FX dummy is statistically significant with a positive coefficient (0.05, $p < 0.1$). The foreign sale ratio coefficient is statistically significant but economically negligible (-0.001). The interaction term between the two variables is not statistically significant, and accordingly, we fail to accept H3.

Panel B presents the interaction results for the IR hedging dummy and the interest coverage variable. Neither variable is statistically significant on its own in the model, and although the interaction term is significant ($p < 0.05$), the coefficient is economically negligible (0.000). Taken together, we fail to accept H4, which contrasts that hedging is more valuable for firms with lower interest coverage and greater interest rate vulnerability (Chen & King, 2014).

Panel C presents the results for the interaction between commodity hedging and commodity-intensive sectors. In this specification, the commodity hedging dummy is statistically significant ($p < 0.01$) with a positive coefficient of 0.115, which is higher than the coefficient in the baseline Model 5 specification (0.087). However, the interaction term is negative and statistically significant at the 10% level (-0.091). This implies that, overall, hedging commodity risk has a positive effect on distance to default, but for firms operating in a commodity-intensive sector, the effect is negatively moderated, which is the opposite effect we expected from the interaction. In line with this result, we fail to accept H5.

Finally, Table 9 presents results for the interaction between Hedgeoverall and the free cash flow-to-asset ratio (FCF/TA) to test H6. While the hedgeoverall variable is insignificant, the FCF/TA variable is statistically significant ($p < 0.01$) with a negative coefficient (-0.554), implying that firms with a higher FCF/TA ratio exhibit a lower distance to default. This is consistent with agency theory, in which excess cash flows may lead to wasted investments (Fauver & Naranjo, 2010). Crucially, the interaction between the two variables is statistically significant ($p < 0.01$) with a positive coefficient (0.341), and we therefore accept H6. Taken together, these findings indicate that the negative effect of a higher FCF/TA ratio is moderated by engaging in any type of hedging through derivatives (Bessembinder, 1991; Fauver & Naranjo, 2010).

5.3 Robustness Models

5.3.1 Lagged Results

Table 10 presents lagged hedging dummies as a robustness check towards the baseline regression results. Panel A presents the results for the specification in which distance to default is the dependent variable. The aggregate lagged hedging indicator (L_Hedgeoverall) loses statistical significance. When the categories are entered in isolation, lagged FX hedging retains a positive and significant coefficient, and lagged commodity hedging remains the strongest predictor. Lagged interest rate hedging is statistically insignificant. In Model (32), where all three categories enter simultaneously, the coefficients on FX (0.039, $p < 0.05$) and commodity hedging (0.076, $p < 0.01$) remain significant, while IR hedging is again insignificant. The pattern from the baseline is therefore similar under the lagged specification, with the commodity effect being the most robust and the IR effect being the weakest. Panels B and C report the corresponding CDS and OAS specifications. None of the lagged hedging indicators are statistically significant in either subsample, mirroring their baseline results.

Another lagged-variable result is presented in Table G, where all explanatory variables are lagged by t-1, both hedging indicators and firm-level controls. In isolation, the disaggregated hedging indicators are significant, but in the joint specification, only the commodity hedging variable remains significant at the 5% level and with a slightly smaller coefficient of 0.073. Overall, the results are similar to those of Chen and King (2014), who found that lagged specifications yielded smaller and less significant hedging effects.

While the lagged variable approach helps separate the timing of hedging decisions from risk outcomes, we acknowledge Roberts and Whited's (2013) critique. They argue that if firm-level variables are persistent, then lagging regressors cannot completely eliminate endogeneity bias. We therefore turn to propensity score matching (PSM) and instrumental variable (IV) in the following sections as an effort to validate the relationship further.

5.3.2 Propensity Score Matching Results

Table 11 presents the first PSM model, in which each treated firm-year is matched 1:1 to its nearest non-treated neighbor on the lagged firm-level controls within a narrow caliper of 0.01. The aggregate hedging indicator (Hedgeoverall) in Panel A presents a positive and significant Average Treatment Effect (ATT) of 0.064 on the distance to default ($p < 0.05$).

The coefficient is lower in the POLS specification of 0.034. This suggest that within the subsample of hedgers and observably comparable non-hedgers, the conditional association between hedging and distance to default is stronger

The category-specific results in Panels B through D follow a similar pattern with statistically significant and larger ATTs than the corresponding POLS coefficients in Table 5 across all categories. An interesting finding is that the CDS spread becomes statistically significant for all three risk categories under PSM and carries the predicted negative sign. Overall, the strongest effects are observed in Panel D for commodity hedging firms. The coefficients are the largest across all panels, and it is the only panel in which the OAS spread is statistically significant.

Appendix E reports a more demanding initiation-and-suspension specification, similar to that of Chen and King (2014). Treated firm-years are restricted to transitions from non-hedger to hedger (initiation) and from hedger to non-hedger (suspension), and matched to control firm-years that are stable in both periods. Most results are insignificant, which is partly expected given the substantially smaller number of qualifying transition events (ranging from 107 to 902). The estimates that do emerge are mixed. For aggregate hedging, suspension events are associated with a significant decline in distance to default (ATT = -0.125, $p < 0.05$), consistent with the prediction that firms ceasing to hedge have a higher default risk. However, the corresponding log CDS result is in the opposite direction of expectations (ATT = -0.109, $p < 0.10$), making the results ambiguous. The clearest signal occurs for interest rate hedging suspension on log OAS spreads (ATT = 0.117, $p < 0.01$), where firms that withdraw interest rate derivatives experience a significant widening of bond yield spreads. This is consistent with the prediction in Section 2.3 that interest rate management is linked to debt-service capacity, as emphasized by Judge et al. (2026). For Panel B (FX hedging) and Panel D (Commodity hedging), no statistically significant initiation or suspension effect is observed.

Taken together, the two propensity score matching specifications support the cross-sectional baseline findings in Table 5 without overturning them. The level-based matching in Table 11 shows that, conditional on observables, commodity, foreign exchange, and interest rate hedgers exhibit lower default risk and lower credit-market spreads than otherwise comparable non-hedgers. Commodity hedging is again the most consistent across measures. The event-based matching in Appendix E produces more ambiguous evidence, possibly since a small number of initiation and suspension events were analyzed, and we therefore interpret the results carefully compared to the other matching. As noted in Roberts and Whited (2013), matching cannot remove selection on unobservable characteristics, and the PSM results are interpreted as evidence of robustness rather than causal estimates.

5.4 Instrument Variable Results

Appendix M reports the 2SLS estimates for the distance to default specification, in which the aggregate hedging indicator is instrumented with the lagged sector-year leave-one-out peer hedging rate. The first-stage Kleibergen-Paap F-statistic of 21.5 exceeds the conventional threshold of 10 proposed by Staiger and Stock (1997), indicating that the instrument is strong in the relevance dimension. Although, as discussed in Section 4.3.4, the exclusion restriction cannot be directly tested and must be justified economically (Roberts & Whited, 2013).

The second-stage coefficient on the aggregate hedging indicator is 1.261 and statistically significant ($p < 0.01$). This magnitude is substantially larger compared to the POLS coefficient of 0.034 (Table 5) and the difference in mean of 0.519 (Table 4). Given that this coefficient implies a 45% increase relative to the sample mean DD of 2.805, the economic implications seem implausible. Consequently, we avoid a direct causal interpretation and are very cautious towards drawing conclusions from these 2SLS results. This large estimate could suggest that the instrument has picked up correlated peer-level shocks that affect default risk through channels other than the firm's own hedging decision. Sector peers tend to share common exposures to interest rate, commodity, and currency fluctuations. If these correlated exposures affect default risk directly, the exclusion restriction is violated, and the 2SLS estimator is inconsistent, and the resulting coefficients are biased (Roberts & Whited, 2013; Wooldridge, 2016).

6. Discussion

This chapter presents the empirical results of the study in light of the literature, develops the interpretation of the conditional findings, discusses the study's limitations, and implications for future research.

6.1 The Aggregate Hedging Effect on Default Risk

The aggregate hedging results require careful interpretation. In the baseline pooled OLS specification, the aggregate hedging indicator yields a significant and positive coefficient implying a 1.2% increase in distance to default for hedging firms. This pattern relates to Magee's (2013) finding that the binary decisions to hedge yield insignificant results regarding default risk. Instead, the statistical effect emerged when hedging was measured at the intensity (notional) level. Since our binary indicator captures the decision to hedge but not the extent, it could explain the observed small economic effect. Further, Magee (2013) studies a sample of large U.S. firms with higher average DD where these larger firms might be less sensitive to binary hedging variables and require notional variables for results. Therefore, our findings can be explained by our broader sample of the Russell 3000 with more firm-level variation. This would also help explain why our hedging variables are not significant in the CDS and OAS subsamples, since these firms are larger overall and different from the DD sample.

The second possible explanation relates to the context of the study. Our sample period (2014–2024) had sustained growth in corporate derivative use, and the global OTC derivatives market reached an all-time high in mid-2025 (Bank for International Settlements, 2025). Although the figure reported is not limited to NFCs, as hedging becomes a near-universal corporate practice rather than a unique policy, cross-sectional variation in the binary indicator decreases. This makes the treatment and control groups become increasingly similar on the underlying dimension we want to measure. Consequently, the positive signaling content of the aggregate hedging decision is weaker in an environment where hedging is the norm. This would lead to a weaker positive effect on DD, when applied to the hedging and signaling relationship proposed by DeMarzo and Duffie (1995).

6.2 Disaggregating Across the Hedging Types

When disaggregating the hedging variables in our sample, more economically and statistically meaningful effects are presented. Commodity hedging is the most consistent association of reducing default risk, significant across POLS, FE, lagged specification, and PSM for distance to default. Foreign exchange hedging also shows significant effects on distance to default under POLS and PSM, but when faced with FE, it loses significance. This could be explained by FX hedging being a slower moving firm-level policy. For instance, Magee (2013) notes that the within-firm standard deviation of FX hedging intensity in his sample is only 3%, and does not include firm fixed effects for this reason. Interest rate hedging is the weakest of the three categories, producing significant effects only in the PSM. This contrasts with Judge et al. (2026)'s finding that interest rate hedging reduces default frequencies the most for European firms. A possible explanation is measurement errors relating to the IR hedging dummy. Our manual audit (Appendix K) shows that the models have the lowest agreement rate for the IR hedging dummy and it is possible that this weakens the results however it is hard to know how the audit results generalize over the full sample.

A reason that could explain why commodity hedging is the most robust predictor of distance to default in our sample is the following: Firms in commodity-intensive industries face exposure to input-cost volatility, which can directly impact operating cash flow (Anbil et al. 2019). Commodity hedgers are also more levered than the average sample firm, and arguably, the benefit of cash flow stability is more valuable for firms whose expected distress costs are higher (Purnanandam, 2008).

6.3 Moderating Hedging Effects

The conditional hypotheses H3 through H6 produce mixed results. We find no consistent evidence that FX hedging yields greater reductions in default risk for foreign sales-exposed firms (H3). This goes against the findings of Allayannis and Weston (2001), who document that the FX hedging firm value premium is concentrated among firms with foreign sales. Similar to Allayannis and Weston (2001), our hedging measure is binary to maintain sample power, and therefore the within-firm variation on which the interaction is identified is limited in our sample. The foreign sales ratio also captures only one dimension of FX exposure. Firms might also be exposed to foreign currency denominated debt, imported inputs, or competition from foreign producers, which none of our variables capture (Allayannis & Ofek, 2001).

The interaction between IR hedging and interest coverage ratio is statistically significant in the DD POLS model but economically zero, and insignificant in all other models (H4). We therefore find no substantial evidence that the default risk effect of IR hedging is conditional on interest coverage. The finding deviates from Chen and King (2014), who show that firms with higher credit risk, those with speculative-grade ratings and lower interest coverage ratios, benefit more from hedging through a greater reduction in borrowing costs.

The most substantial finding is found in the interaction between commodity hedging and the commodity-intensive sector indicator (H5). The interaction coefficient is negative, indicating that default risk is increased by commodity hedging in commodity-intensive sectors, which is the opposite of the hypothesized direction. This is an interesting finding, but not economically intuitive since the hypothesis was that firms exposed to commodity price volatility should benefit from mitigating this risk. However, Giambona et al. (2018) demonstrate that operational hedging dominates financial hedging across commodity exposure. Companies within commodity-intensive sectors, such as mining and petroleum refining, might manage their exposure through long-term supply contracts, vertical integration, geographical diversification, and inventory management. This can leave little benefit for financial derivatives, similar to Jin & Jorion's (2006) lack of hedging premium for oil and gas firms.

Firms outside these sectors that still have commodity exposure, such as manufacturing firms exposed to metal prices, may have fewer operational substitutes available and hence benefit more from financial derivatives. Another argument highlights the basis risk documented by Gilje and Taillard (2017), where hedging effectiveness declines when the financial instruments available are imperfect substitutes for the underlying exposure. In the commodity-intensive sectors, underlying exposure might be more specific than easily available standardized contracts. In this argument, financial hedges carry more basis risk and produce a smaller risk-reducing effect.

Finally, the agency cost interaction is supported, leading us to accept H6. The coefficient on the free cash flow to assets ratio is negative, meaning that, conditional on the other controls, firms with a higher free cash flow to assets ratio exhibit a lower distance to default. In isolation, this result would be consistent with Jensen's (1986) free cash flow agency cost hypothesis. The interaction term, however, is positive and moderates the negative effect. This result suggests that hedging absorbs a portion of the agency-cost penalty associated with default risk, consistent with the theoretical arguments of Bessembinder (1991) and Campbell and Kracaw (1990). By being able to meet its debt obligations in adverse states and reducing risk-shifting incentives, the firm mitigates the shareholder and creditor conflict through hedging. The H6 result stays robust when excluding the profitability control, which was highly correlated with the free cash flow ratio. Importantly, the result does not hold under firm fixed effects, where the interaction coefficients turn negative and statistically insignificant. This is interpreted as agency cost moderation arising from cross-sectional differences between high- and low agency cost firms, rather than from within-firm hedging changes over time.

6.4 Limitations

The main limitation is that our hedging classification relies on automated natural-language extraction from 10-K filings rather than on direct disclosure of derivative positions in the financial report. A manual audit of the model against randomly drawn firm-year observations obtains a classification accuracy of 90%, detailed in Appendix H-K. However, the binary indicators lose information about a firm's hedging intensity, which would be highly desired. As shown by Magee (2013), the binary decision to hedge failed to show a connection to default risk and was instead captured by hedging intensity. The weak coefficients on our aggregate hedging dummy could imply that the binary variable is less informative than an intensity measure. As mentioned, in the initial phases of the study, we attempted to extract notional amounts for scaling against firm size. This effort was abandoned after manual auditing revealed that it was inconsistent and could be collected from only a minuscule share of the full sample. We hope future research using hand-collected samples or improved models can study hedging intensity at scale.

Furthermore, our hedging indicators do not distinguish between designated and non-designated positions. Anbil et al. (2019) document that credit market perceptions, specifically CDS spreads, depend on whether positions are designated as accounting hedges or not. The lack of results in the CDS subsample might reflect this limitation in our study. Future research could also attempt to extract the designation status of the derivative positions, and therefore see if results could be impacted by hedge accounting.

For the main dependent variable, Merton's (1974) distance to default, there are shortcomings. Jessen and Lando (2015) examine the sensitivity of DD to relaxations of its assumptions and highlight that its accuracy worsens when asset values experience large jumps. They conclude that DD remains a strong predictor of default under realistic conditions, though the underlying assumptions remain limiting. Furthermore, research by Bharath & Shumway (2008) suggests the model is not a "sufficient statistic" for forecasting bankruptcy and does not capture past equity returns. Instead, they found the "naïve" alternative to perform better, but we chose the procedure outlined in Section 3.2 to remain comparable to the hedging literature (Magee, 2013; Campello et al. 2011). Another concern is that DD can only be constructed for firms with observable leverage and sufficient equity-return history. We lose approximately 25% of the firm-year observations in the Russell 3000 compared to the main sample. The historical constituent list extraction was an effort to reduce selection bias, but firms that are delisted or merged during the sample period may still be underrepresented. Similarly, survivorship bias might have impacted results since we lose Russell 3000 firms that are excluded from the index due to actual default.

The CDS and OAS subsamples are selected based on credit market presence and consist of larger, higher-rated firms. If the default risk benefit from hedging is concentrated among smaller and more credit-constrained firms whose cash flow stabilization might be more valuable, our credit market specifications are systematically biased against an observed hedging effect. This concern is also raised by Anbil et al. (2019) for their S&P 500 sample.

Of the classical market frictions outlined in Section 2.1, the financial-distress channel is captured by the distance to default measure itself, and the agency conflict is captured by the FCF/TA interaction in H6. This leaves the financing friction and information asymmetry not identified separately, since standard proxies, such as analyst forecast dispersion for information asymmetry, and measures of financing frictions, were unavailable for reliable data retrieval.

Despite the use of firm fixed effects, instrumental variables, and propensity score matching, we cannot rule out that the hedging coefficient absorbs unobserved firm characteristics correlated with hedging policy. As discussed in Section 5.4, the peer hedging rate instrument satisfies the relevance condition, but the implausibly large second-stage coefficient suggests that the exclusion restriction is likely violated. Additional instruments and identification strategies could strengthen the causal inference.

7. Conclusion

This chapter summarizes the findings and presents the study's conclusions.

This paper studies whether corporate hedging with derivatives reduces default risk for U.S. nonfinancial firms from 2014 to 2024. For a sample of 3,757 unique Russell 3000 firms, hedging indicators were collected through automated text extraction from 10-K SEC filings. In the paper, we estimate the effect of hedging on one main default risk measurement, the Merton (1974) distance to default, along with two complementary measures, the five-year credit default swap (CDS) spreads and option-adjusted bond yield spreads (OAS).

The aggregate decision to hedge only has a small and weakly significant association with distance to default and an insignificant association with credit-market spreads in baseline regressions. However, when disaggregating by hedge type, results reveal that commodity hedging is robustly associated with a reduced default risk across multiple specifications. Foreign exchange hedging produces consistent effects in POLS and propensity score matching, but is absorbed by firm fixed effects, and interest rates show the weakest effects of the three categories. Our findings also suggest that under POLS the aggregate hedging can moderate negative effects on distance to default from agency problems, consistent with theories by Bessembinder (1991) and Campbell and Kracaw (1990).

The propensity-score matching shows a stronger effect than the unmatched regressions, particularly for CDS spread, indicating that the matched subsample finds effects that do not generalize over the full sample. These findings support the Smith and Stulz (1985) hypothesis that risk management reduces the expected costs of financial distress, but they differ from the magnitudes of the effects documented by Magee (2013), Chen and King (2014), and Judge et al. (2026).

Future research could extend this work in several dimensions, most notably by enabling notional amount extraction. Event study designs around exogenous shocks to hedge effectiveness could provide cleaner causal identification than the IV strategy employed here. Finally, extending the analysis to non-U.S. jurisdictions where disclosure regulations differ could shed light on whether the results we document are specific to the U.S. setting or reflect a broader shift in the hedging-credit relationship.

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Tables

Table 1: Full-Sample Summary Statistics

	N	*Mean*	*Median*	*SD*	*Min*	*Max*
Panel A: Dependent Variables and Hedging Dummies						
Distance to default	16,205	2.805	2.617	1.298	-1.292	6.604
Ln_CDS	5,431	4.843	4.718	0.965	2.917	7.253
Ln_OAS	4,281	5.125	5.087	0.665	2.099	8.461
Hedging Dummy	21,508	0.544	1.000	0.498	0.000	1.000
FX Hedging Dummy	21,508	0.403	0.000	0.490	0.000	1.000
IR Hedging Dummy	21,508	0.441	0.000	0.497	0.000	1.000
Commodity Hedging Dummy	21,508	0.154	0.000	0.361	0.000	1.000
Panel B: Firm-Level Control Variables						
Leverage	21,484	0.288	0.265	0.237	0.000	1.134
Total Assets (Millions)	21,508	8611.174	1509.673	29804.768	0.150	624894.000
Profitability	21,398	0.038	0.095	0.215	-0.873	0.387
Cash Holdings	21,473	0.166	0.101	0.189	0.001	0.923
Tangibility	21,393	0.219	0.135	0.221	0.002	0.901
Tobin's Q	21,178	2.303	1.592	2.044	0.451	12.041
1-Year Stock Return Volatility (%)	20,228	46.622	40.028	24.499	15.143	137.709
Panel C: Interaction Moderators						
Foreign income share (%)	20,057	25.816	17.747	27.257	0.000	98.983
Interest Coverage	18,237	19.153	7.131	217.550	-1,222.250	1,321.045
Free Cash Flow / Total Assets	21,264	-0.003	0.040	0.173	-0.753	0.275
Commodity intensive sector dummy	21,508	0.121	0.000	0.326	0.000	1.000

Table 2: Means of Variables by Sector and Year

	N	*Hedgeoverall*	*FXoverall*	*Iroverall*	*Comdoverall*	*dist_default*	*Ln_CDS*	*Ln_OAS*
Panel A: Means by Year								
2014	1,084	.532	.399	.424	.176	3.554	4.972	5.137
2015	1,338	.526	.410	.439	.157	3.284	4.959	5.452
2016	1,433	.534	.415	.431	.160	2.979	4.910	5.138
2017	1,467	.555	.426	.457	.164	3.574	4.691	4.831
2018	1,490	.548	.417	.453	.160	2.897	4.984	5.338
2019	1,485	.531	.393	.432	.160	2.926	4.712	4.826
2020	1,497	.545	.396	.446	.145	1.728	4.811	5.053
2021	1,551	.550	.389	.444	.141	2.640	4.766	5.056
2022	1,618	.573	.402	.455	.146	2.265	5.065	5.394
2023	1,590	.543	.399	.435	.146	2.594	4.823	5.138
2024	1,557	.538	.389	.432	.147	2.760	4.611	5.049
Panel B: Means by Sector								
Communication Services	880	.521	.315	.391	.022	2.729	4.958	5.284
Consumer Discretionary	2,701	.542	.373	.460	.130	2.765	5.062	5.236
Consumer Staples	996	.687	.509	.603	.437	3.666	4.373	4.768
Energy	1,045	.736	.295	.599	.294	2.193	5.492	5.521
Financials *	237	.609	.522	.547	.103	3.396	4.623	4.914
Health Care	2,950	.336	.224	.244	.029	2.360	4.448	4.892
Industrials	3,654	.644	.522	.562	.222	3.085	4.787	5.137
Information Technology	2,391	.531	.478	.374	.052	2.731	4.641	4.940
Materials	1,194	.756	.665	.659	.496	3.030	4.895	5.310
Real Estate	54	.493	.164	.478	.015	3.490	4.112	5.194

N denotes the number of firm-year observations in the baseline regression sample (non-missing on distance to default and all baseline controls). * Financials are firms without SIC code 6000-6999

Table 3: Pairwise Correlation Matrix

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*	*(17)*	*(18)*
(1) dist_default	1.000																	
(2) Ln_CDS	-0.605***	1.000																
(3) Ln_OAS	-0.526***	0.790***	1.000															
(4) Hedgeoverall	0.192***	-0.133***	-0.097***	1.000														
(5) FXoverall	0.276***	-0.277***	-0.210***	0.728***	1.000													
(6) Iroverall	0.219***	-0.160***	-0.113***	0.788***	0.640***	1.000												
(7) Comdoverall	0.171***	-0.097***	-0.077***	0.380***	0.344***	0.382***	1.000											
(8) Leverage	-0.126***	0.322***	0.265***	0.211***	0.121***	0.239***	0.115***	1.000										
(9) Size	0.437***	-0.581***	-0.522***	0.430***	0.433***	0.450***	0.297***	0.278***	1.000									
(10) Profitability	0.411***	-0.268***	-0.245***	0.269***	0.258***	0.289***	0.173***	0.129***	0.474***	1.000								
(11) CashHoldings	-0.252***	-0.047***	-0.040***	-0.259***	-0.220***	-0.295***	-0.196***	-0.254***	-0.472***	-0.509***	1.000							
(12) Tangibility	-0.054***	0.203***	0.189***	0.121***	-0.039***	0.126***	0.204***	0.206***	0.198***	0.252***	-0.310***	1.000						
(13) TobinsQ	0.038***	-0.356***	-0.369***	-0.165***	-0.114***	-0.174***	-0.144***	-0.092***	-0.229***	-0.152***	0.361***	-0.209***	1.000					
(14) StockVolatility	-0.848***	0.569***	0.509***	-0.217***	-0.281***	-0.247***	-0.159***	0.024***	-0.427***	-0.553***	0.354***	-0.025***	0.046***	1.000				
(15) ForeignShare	0.150***	-0.207***	-0.191***	0.236***	0.412***	0.207***	0.123***	-0.019***	0.226***	0.125***	-0.012*	-0.125***	0.024***	-0.162***	1.000			
(16) IntCoverage	0.135***	-0.082***	-0.080***	0.041***	0.042***	0.026***	0.013*	-0.060***	0.091***	0.340***	-0.160***	0.059***	-0.016**	-0.195***	0.015*	1.000		
(17) FCF_TA	0.395***	-0.397***	-0.373***	0.223***	0.251***	0.234***	0.114***	0.042***	0.428***	0.896***	-0.402***	0.071***	-0.062***	-0.522***	0.147***	0.292***	1.000	
(18) CommIntensive	-0.053***	0.187***	0.201***	0.150***	0.057***	0.140***	0.248***	0.058***	0.140***	0.133***	-0.172***	0.492***	-0.179***	0.004	0.039***	0.005	0.037***	1.000

* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 4: Univariate t-tests: Hedgers vs Non-Hedgers

	Hedgers (=1)		*Non-Hedgers (=0)*				
	N	*Mean*	*N*	*Mean*	*Diff (NH-H))*	*t-stat*	*p-value*
Panel A: Hedgeoverall (any hedging)							
dist_default	10,287	2.995	5,918	2.476	-0.519***	-25.630	0.000
Ln_CDS	4,142	4.772	1,289	5.073	0.301***	9.581	0.000
Ln_OAS	3,367	5.091	914	5.248	0.157***	6.240	0.000
Leverage	11,693	0.334	9,791	0.234	-0.100***	-31.211	0.000
Size	11,697	14.995	9,811	13.485	-1.510***	-69.882	0.000
Profitability	11,656	0.091	9,742	-0.025	-0.116***	-39.021	0.000
CashHoldings	11,673	0.121	9,800	0.219	0.098***	37.734	0.000
Tangibility	11,658	0.244	9,735	0.190	-0.054***	-17.950	0.000
TobinsQ	11,542	1.995	9,636	2.671	0.676***	23.663	0.000
StockVolatility	11,202	41.840	9,026	52.557	10.717***	31.176	0.000
ForeignShare	11,256	31.514	8,801	18.560	-12.954***	-34.592	0.000
IntCoverage	10,938	26.378	7,299	8.326	-18.053***	-4.883	0.000
CommIntensive	11,697	0.166	9,811	0.067	-0.098***	-23.063	0.000
FCF_TA	11,632	0.032	9,632	-0.046	-0.078***	-31.845	0.000
Panel B: FXoverall (FX hedging)							
dist_default	7,748	3.180	8,457	2.462	-0.718***	-36.405	0.000
Ln_CDS	3,422	4.638	2,009	5.193	0.554***	20.609	0.000
Ln_OAS	2,896	5.028	1,385	5.327	0.299***	13.508	0.000
Leverage	8,660	0.323	12,824	0.265	-0.058***	-18.672	0.000
Size	8,663	15.230	12,845	13.683	-1.547***	-70.664	0.000
Profitability	8,646	0.105	12,752	-0.008	-0.113***	-44.500	0.000
CashHoldings	8,662	0.115	12,811	0.200	0.085***	36.920	0.000
Tangibility	8,641	0.209	12,752	0.226	0.018***	6.029	0.000
TobinsQ	8,572	2.019	12,606	2.496	0.477***	17.685	0.000
StockVolatility	8,364	38.414	11,864	52.409	13.995***	43.765	0.000
ForeignShare	8,444	38.984	11,613	16.266	-22.718***	-63.789	0.000
IntCoverage	8,190	29.223	10,047	10.945	-18.278***	-5.973	0.000
CommIntensive	8,663	0.144	12,845	0.106	-0.038***	-8.175	0.000
FCF/TA	8,642	0.049	12,622	-0.039	-0.088***	-42.667	0.000
Panel C: Iroverall (IR hedging)							
dist_default	8,690	3.069	7,515	2.501	-0.569***	-28.682	0.000
Ln_CDS	3,702	4.738	1,729	5.069	0.330***	11.702	0.000
Ln_OAS	3,028	5.076	1,253	5.241	0.165***	7.259	0.000
Leverage	9,483	0.352	12,001	0.238	-0.114***	-36.750	0.000
Size	9,487	15.193	12,021	13.606	-1.587***	-74.159	0.000
Profitability	9,455	0.108	11,943	-0.018	-0.125***	-47.623	0.000
CashHoldings	9,466	0.103	12,007	0.215	0.112***	48.322	0.000
Tangibility	9,457	0.251	11,936	0.194	-0.056***	-18.440	0.000
TobinsQ	9,370	1.903	11,808	2.620	0.717***	26.768	0.000
StockVolatility	9,130	39.945	11,098	52.116	12.171***	37.066	0.000
ForeignShare	9,183	31.960	10,874	20.653	-11.307***	-29.876	0.000
IntCoverage	9,086	24.749	9,151	13.598	-11.151***	-3.470	0.001
CommIntensive	9,487	0.172	12,021	0.080	-0.092***	-20.024	0.000
FCF/TA	9,448	0.042	11,816	-0.039	-0.082***	-37.525	0.000
Panel D: Comdoverall (commodity hedging)							
dist_default	3,103	3.262	13,102	2.697	-0.565***	-20.711	0.000
Ln_CDS	1,684	4.703	3,747	4.906	0.203***	7.243	0.000
Ln_OAS	1,419	5.052	2,862	5.160	0.108***	5.019	0.000
Leverage	3,311	0.352	18,173	0.277	-0.075***	-19.969	0.000
Size	3,311	15.525	18,197	14.085	-1.441***	-50.168	0.000
Profitability	3,305	0.125	18,093	0.022	-0.103***	-45.925	0.000
CashHoldings	3,298	0.079	18,175	0.182	0.103***	51.003	0.000
Tangibility	3,308	0.325	18,085	0.200	-0.125***	-28.508	0.000
TobinsQ	3,267	1.613	17,911	2.429	0.815***	31.724	0.000
StockVolatility	3,193	37.636	17,035	48.307	10.671***	26.775	0.000
ForeignShare	3,213	33.482	16,844	24.370	-9.112***	-17.871	0.000
IntCoverage	3,254	25.328	14,983	17.812	-7.516***	-2.790	0.005
CommIntensive	3,311	0.310	18,197	0.086	-0.224***	-26.968	0.000
FCF/TA	3,310	0.043	17,954	-0.012	-0.054***	-27.398	0.000

Two-sample t-test with unequal variances.
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 5: Baseline Hedging and Distance to Default

	(1)	(2)	(3)	(4)	(5)
	dist_default	*dist_default*	*dist_default*	*dist_default*	*dist_default*
Panel A: Pooled OLS					
Hedgeoverall	0.034** (0.017)				
Iroverall		0.040** (0.017)			-0.003 (0.018)
FXoverall			0.065*** (0.019)		0.050** (0.020)
Comdoverall				0.100*** (0.025)	0.087*** (0.025)
Leverage	-0.159*** (0.039)	-0.162*** (0.039)	-0.157*** (0.038)	-0.159*** (0.038)	-0.160*** (0.039)
Size	0.139*** (0.008)	0.139*** (0.008)	0.135*** (0.008)	0.137*** (0.007)	0.133*** (0.008)
Profitability	-0.207*** (0.061)	-0.209*** (0.061)	-0.213*** (0.061)	-0.204*** (0.061)	-0.213*** (0.060)
CashHoldings	0.093 (0.062)	0.098 (0.062)	0.092 (0.062)	0.101* (0.061)	0.098 (0.061)
Tangibility	0.002 (0.058)	0.003 (0.058)	0.013 (0.058)	-0.015 (0.058)	-0.006 (0.058)
TobinsQ	0.044*** (0.006)	0.044*** (0.006)	0.044*** (0.006)	0.045*** (0.006)	0.045*** (0.006)
StockVolatility	-0.040*** (0.001)	-0.040*** (0.001)	-0.040*** (0.001)	-0.040*** (0.001)	-0.040*** (0.001)
_cons	3.181*** (0.169)	3.184*** (0.169)	3.217*** (0.165)	3.206*** (0.170)	3.240*** (0.168)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	16110	16110	16110	16110	16110
Adj/Within R^2	0.763	0.764	0.764	0.764	0.764
Panel B: Firm Fixed Effects					
Hedgeoverall	0.032* (0.017)				
Iroverall		0.016 (0.016)			0.009 (0.017)
FXoverall			0.016 (0.019)		0.003 (0.021)
Comdoverall				0.048** (0.024)	0.044* (0.024)
Leverage	-0.073 (0.053)	-0.072 (0.053)	-0.070 (0.053)	-0.069 (0.053)	-0.070 (0.053)
Size	0.001 (0.019)	0.002 (0.019)	0.002 (0.019)	0.003 (0.019)	0.002 (0.019)
Profitability	0.137* (0.075)	0.138* (0.075)	0.141* (0.075)	0.141* (0.075)	0.140* (0.075)
CashHoldings	0.111 (0.071)	0.111 (0.071)	0.111 (0.071)	0.112 (0.071)	0.112 (0.071)
Tangibility	0.215* (0.116)	0.213* (0.116)	0.214* (0.116)	0.214* (0.116)	0.214* (0.116)
TobinsQ	0.008 (0.006)	0.008 (0.006)	0.008 (0.006)	0.008 (0.006)	0.008 (0.006)
StockVolatility	-0.036*** (0.001)	-0.036*** (0.001)	-0.036*** (0.001)	-0.036*** (0.001)	-0.036*** (0.001)
_cons	4.708*** (0.279)	4.699*** (0.278)	4.698*** (0.278)	4.677*** (0.277)	4.685*** (0.279)
Industry FE	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
Method	FE	FE	FE	FE	FE
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	16110	16110	16110	16110	16110
Adj/Within R^2	0.640	0.640	0.640	0.640	0.640

Standard errors clustered at the firm level reported next to each coefficient in parentheses. Panel A: Pooled OLS with industry and year fixed effects. Panel B: Firm fixed effects with year fixed effects.
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 6: Hedging and Ln(CDS Spread)

	(6)	(7)	(8)	(9)	(10)
	Ln_CDS	*Ln_CDS*	*Ln_CDS*	*Ln_CDS*	*Ln_CDS*
Panel A: Pooled OLS with Industry & Year FE					
Hedgeoverall	0.015 (0.030)				
Iroverall		-0.008 (0.026)			0.006 (0.035)
FXoverall			-0.017 (0.034)		-0.012 (0.043)
Comdoverall				-0.035 (0.032)	-0.034 (0.034)
Leverage	1.051*** (0.094)	1.053*** (0.094)	1.052*** (0.094)	1.056*** (0.094)	1.055*** (0.094)
Size	-0.301*** (0.014)	-0.299*** (0.014)	-0.298*** (0.014)	-0.299*** (0.014)	-0.298*** (0.014)
Profitability	-1.467*** (0.215)	-1.462*** (0.214)	-1.464*** (0.215)	-1.470*** (0.215)	-1.472*** (0.215)
CashHoldings	-0.222 (0.157)	-0.219 (0.158)	-0.215 (0.157)	-0.230 (0.158)	-0.227 (0.157)
Tangibility	0.143 (0.133)	0.143 (0.133)	0.140 (0.133)	0.152 (0.134)	0.150 (0.134)
TobinsQ	-0.104*** (0.014)	-0.105*** (0.014)	-0.105*** (0.014)	-0.105*** (0.014)	-0.105*** (0.014)
StockVolatility	0.017*** (0.001)	0.017*** (0.001)	0.017*** (0.001)	0.017*** (0.001)	0.017*** (0.001)
_cons	9.003*** (0.319)	8.999*** (0.316)	8.994*** (0.316)	9.016*** (0.313)	9.012*** (0.313)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	5242	5242	5242	5242	5242
Adj/Within R^2	0.687	0.687	0.687	0.687	0.687
Panel B: Firm Fixed Effects					
Hedgeoverall	0.004 (0.023)				
Iroverall		0.028 (0.020)			0.034 (0.025)
FXoverall			0.015 (0.024)		0.000 (0.032)
Comdoverall				-0.024 (0.029)	-0.034 (0.031)
Leverage	0.681*** (0.110)	0.678*** (0.110)	0.681*** (0.110)	0.680*** (0.110)	0.675*** (0.111)
Size	-0.199*** (0.036)	-0.200*** (0.036)	-0.199*** (0.036)	-0.198*** (0.036)	-0.200*** (0.036)
Profitability	-1.029*** (0.165)	-1.034*** (0.165)	-1.029*** (0.165)	-1.027*** (0.165)	-1.033*** (0.165)
CashHoldings	-0.290** (0.140)	-0.293** (0.140)	-0.290** (0.140)	-0.288** (0.141)	-0.290** (0.140)
Tangibility	-0.442** (0.205)	-0.443** (0.205)	-0.442** (0.205)	-0.444** (0.205)	-0.445** (0.205)
TobinsQ	-0.077*** (0.012)	-0.077*** (0.012)	-0.077*** (0.012)	-0.077*** (0.012)	-0.077*** (0.012)
StockVolatility	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)
_cons	7.874*** (0.584)	7.880*** (0.581)	7.875*** (0.583)	7.878*** (0.584)	7.888*** (0.580)
Industry FE	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
Method	FE	FE	FE	FE	FE
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	5242	5242	5242	5242	5242
Adj/Within R^2	0.234	0.234	0.234	0.234	0.235

Standard errors clustered at the firm level reported next to each coefficient in parentheses. Panel A: Pooled OLS with industry and year fixed effects. Panel B: Firm fixed effects with year fixed effects.

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

Table 7: Hedging and Ln(OAS Spread)

	(11)	(12)	(13)	(14)	(15)
	Ln_OAS	*Ln_OAS*	*Ln_OAS*	*Ln_OAS*	*Ln_OAS*
Panel A: Pooled OLS with Industry & Year FE					
Hedgeoverall	0.017 (0.026)				
Iroverall		0.014 (0.023)			0.021 (0.029)
FXoverall			0.003 (0.026)		-0.007 (0.033)
Comdoverall				-0.008 (0.024)	-0.011 (0.025)
Leverage	0.792*** (0.080)	0.791*** (0.080)	0.793*** (0.080)	0.794*** (0.080)	0.791*** (0.080)
Size	-0.190*** (0.011)	-0.190*** (0.011)	-0.189*** (0.011)	-0.189*** (0.011)	-0.189*** (0.011)
Profitability	-1.196*** (0.155)	-1.197*** (0.155)	-1.193*** (0.155)	-1.195*** (0.154)	-1.202*** (0.154)
CashHoldings	-0.163 (0.125)	-0.160 (0.126)	-0.161 (0.125)	-0.163 (0.126)	-0.164 (0.126)
Tangibility	0.075 (0.088)	0.077 (0.088)	0.077 (0.088)	0.079 (0.089)	0.079 (0.089)
TobinsQ	-0.083*** (0.010)	-0.083*** (0.010)	-0.083*** (0.010)	-0.083*** (0.009)	-0.083*** (0.009)
StockVolatility	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)
_cons	8.277*** (0.207)	8.283*** (0.208)	8.276*** (0.207)	8.275*** (0.207)	8.283*** (0.208)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	4236	4236	4236	4236	4236
Adj/Within R^2	0.684	0.684	0.684	0.684	0.684
Panel B: Firm Fixed Effects					
Hedgeoverall	0.038 (0.024)				
Iroverall		0.015 (0.021)			0.010 (0.024)
FXoverall			0.020 (0.025)		0.018 (0.029)
Comdoverall				-0.010 (0.026)	-0.017 (0.026)
Leverage	0.775*** (0.101)	0.775*** (0.100)	0.778*** (0.100)	0.779*** (0.101)	0.773*** (0.100)
Size	-0.124*** (0.030)	-0.124*** (0.030)	-0.123*** (0.030)	-0.123*** (0.030)	-0.123*** (0.030)
Profitability	-1.116*** (0.155)	-1.116*** (0.155)	-1.112*** (0.155)	-1.111*** (0.155)	-1.116*** (0.155)
CashHoldings	-0.195 (0.128)	-0.196 (0.129)	-0.194 (0.129)	-0.193 (0.129)	-0.193 (0.129)
Tangibility	-0.094 (0.189)	-0.099 (0.190)	-0.098 (0.190)	-0.101 (0.190)	-0.100 (0.190)
TobinsQ	-0.024** (0.012)	-0.023* (0.012)	-0.023* (0.012)	-0.024* (0.012)	-0.023* (0.012)
StockVolatility	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)
_cons	6.974*** (0.511)	6.988*** (0.510)	6.976*** (0.511)	6.986*** (0.511)	6.985*** (0.510)
Industry FE	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
Method	FE	FE	FE	FE	FE
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	4236	4236	4236	4236	4236
Adj/Within R^2	0.426	0.426	0.426	0.426	0.426

Standard errors clustered at the firm level reported next to each coefficient in parentheses. Panel A: Pooled OLS with industry and year fixed effects. Panel B: Firm fixed effects with year fixed effects.
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 8: Hedging × Moderator Exposure Interactions

	(16) DD POLS	(17) DD FE	(18) CDS POLS	(19) CDS FE	(20) OAS POLS	(21) OAS FE
Panel A: FX Hedging × Foreign Income Share						
FXoverall	0.050* (0.028)	-0.009 (0.030)	-0.031 (0.060)	0.042 (0.048)	0.059 (0.044)	0.074** (0.037)
ForeignShare	-0.001** (0.000)	-0.000 (0.001)	0.000 (0.001)	0.001 (0.002)	0.001 (0.001)	-0.002 (0.001)
FX_x_Foreign	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	-0.001 (0.001)	-0.002** (0.001)	-0.001 (0.001)
Iroverall	-0.009 (0.018)	0.007 (0.018)	0.000 (0.036)	0.031 (0.025)	0.027 (0.030)	0.014 (0.025)
Comdoverall	0.090*** (0.025)	0.048** (0.024)	-0.027 (0.033)	-0.038 (0.031)	-0.014 (0.024)	-0.028 (0.026)
Leverage	-0.131*** (0.040)	-0.076 (0.057)	1.056*** (0.096)	0.662*** (0.112)	0.805*** (0.081)	0.808*** (0.099)
Size	0.134*** (0.008)	-0.000 (0.019)	-0.300*** (0.015)	-0.195*** (0.036)	-0.187*** (0.011)	-0.123*** (0.031)
Profitability	-0.176*** (0.063)	0.129 (0.080)	-1.419*** (0.215)	-1.030*** (0.167)	-1.194*** (0.158)	-1.123*** (0.157)
CashHoldings	0.127** (0.064)	0.079 (0.075)	-0.258 (0.160)	-0.268* (0.140)	-0.134 (0.127)	-0.176 (0.130)
Tangibility	-0.007 (0.059)	0.225* (0.121)	0.162 (0.139)	-0.302 (0.195)	0.098 (0.090)	-0.051 (0.192)
TobinsQ	0.042*** (0.007)	0.008 (0.006)	-0.105*** (0.014)	-0.075*** (0.012)	-0.082*** (0.010)	-0.025** (0.012)
StockVolatility	-0.041*** (0.001)	-0.037*** (0.001)	0.017*** (0.001)	0.008*** (0.001)	0.012*** (0.001)	0.007*** (0.001)
_cons	3.277*** (0.171)	4.779*** (0.285)	9.015*** (0.316)	7.746*** (0.586)	8.217*** (0.210)	7.035*** (0.509)
Industry FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Method	POLS	FE	POLS	FE	POLS	FE
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	15451	15451	5152	5152	4161	4161
Adj/Within R^2	0.766	0.644	0.688	0.234	0.685	0.427
Panel B: IR Hedging × Interest Coverage						
Iroverall	-0.012 (0.018)	0.007 (0.018)	0.012 (0.036)	0.035 (0.026)	0.018 (0.030)	0.005 (0.026)
IntCoverage	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
IR_x_IntCov	0.000** (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
FXoverall	0.053*** (0.020)	-0.003 (0.022)	-0.017 (0.044)	0.001 (0.032)	-0.004 (0.034)	0.021 (0.029)
Comdoverall	0.086*** (0.025)	0.040* (0.024)	-0.033 (0.034)	-0.034 (0.031)	-0.014 (0.024)	-0.019 (0.026)
Leverage	-0.160*** (0.039)	-0.076 (0.055)	1.040*** (0.096)	0.667*** (0.113)	0.787*** (0.081)	0.750*** (0.101)
Size	0.132*** (0.008)	-0.001 (0.019)	-0.298*** (0.014)	-0.202*** (0.037)	-0.189*** (0.011)	-0.126*** (0.031)
Profitability	-0.209*** (0.063)	0.158** (0.078)	-1.457*** (0.221)	-1.018*** (0.168)	-1.193*** (0.156)	-1.136*** (0.158)
CashHoldings	0.086 (0.063)	0.105 (0.073)	-0.232 (0.157)	-0.303** (0.141)	-0.128 (0.126)	-0.167 (0.130)
Tangibility	-0.007 (0.059)	0.219* (0.120)	0.141 (0.135)	-0.461** (0.205)	0.086 (0.089)	-0.095 (0.190)
TobinsQ	0.047*** (0.007)	0.008 (0.006)	-0.106*** (0.014)	-0.081*** (0.012)	-0.087*** (0.009)	-0.029** (0.012)
StockVolatility	-0.040*** (0.001)	-0.036*** (0.001)	0.017*** (0.001)	0.008*** (0.001)	0.012*** (0.001)	0.007*** (0.001)
_cons	3.220*** (0.186)	4.760*** (0.288)	9.007*** (0.315)	7.920*** (0.592)	8.283*** (0.207)	7.029*** (0.517)
Industry FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Method	POLS	FE	POLS	FE	POLS	FE
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	15642	15642	5138	5138	4159	4159
Adj/Within R^2	0.765	0.640	0.685	0.230	0.685	0.420
Panel C: Commodity Hedging × Commodity-Intensive Sector						
Comdoverall	0.115*** (0.031)	0.019 (0.030)	-0.054 (0.043)	0.004 (0.035)	-0.030 (0.029)	-0.029 (0.035)
CommIntensive	-0.001 (0.050)	0.000 (.)	0.019 (0.064)	0.000 (.)	0.051 (0.052)	0.000 (.)
Comm_x_Sector	-0.091* (0.051)	0.077 (0.048)	0.063 (0.059)	-0.096 (0.062)	0.063 (0.048)	0.031 (0.053)
Iroverall	-0.003 (0.018)	0.009 (0.017)	0.007 (0.035)	0.033 (0.025)	0.022 (0.029)	0.011 (0.025)
FXoverall	0.050** (0.020)	0.005 (0.021)	-0.011 (0.043)	-0.003 (0.032)	-0.007 (0.033)	0.019 (0.029)
Leverage	-0.161*** (0.039)	-0.069 (0.053)	1.059*** (0.095)	0.669*** (0.111)	0.799*** (0.080)	0.776*** (0.100)
Size	0.132*** (0.008)	0.002 (0.019)	-0.297*** (0.014)	-0.200*** (0.036)	-0.187*** (0.011)	-0.124*** (0.031)
Profitability	-0.205*** (0.062)	0.140* (0.075)	-1.465*** (0.215)	-1.031*** (0.166)	-1.197*** (0.154)	-1.116*** (0.155)
CashHoldings	0.095 (0.061)	0.111 (0.071)	-0.231 (0.157)	-0.287** (0.141)	-0.168 (0.125)	-0.195 (0.129)
Tangibility	0.006 (0.059)	0.214* (0.116)	0.134 (0.137)	-0.440** (0.204)	0.049 (0.091)	-0.102 (0.190)
TobinsQ	0.045*** (0.006)	0.008 (0.006)	-0.104*** (0.014)	-0.077*** (0.012)	-0.081*** (0.009)	-0.023* (0.012)
StockVolatility	-0.040*** (0.001)	-0.036*** (0.001)	0.017*** (0.001)	0.008*** (0.001)	0.012*** (0.001)	0.007*** (0.001)
_cons	3.248*** (0.168)	4.690*** (0.279)	8.943*** (0.330)	7.885*** (0.579)	8.196*** (0.217)	6.991*** (0.512)
Industry FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Method	POLS	FE	POLS	FE	POLS	FE
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	16110	16110	5242	5242	4236	4236
Adj/Within R^2	0.764	0.640	0.687	0.232	0.685	0.423

*Standard errors clustered at the firm level reported next to each coefficient in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 9: Hedgeoverall × Free Cash Flow to total assets

	(22)	(23)	(24)	(25)	(26)	(27)
	DD POLS	*DD FE*	*CDS POLS*	*CDS FE*	*OAS POLS*	*OAS FE*
Hedgeoverall	0.027 (0.017)	0.033** (0.017)	0.015 (0.037)	0.016 (0.026)	0.006 (0.031)	0.026 (0.028)
FCF/TA	-0.554*** (0.117)	0.182 (0.115)	-0.845** (0.338)	-0.136 (0.260)	-0.859*** (0.288)	-0.691** (0.274)
Hedge x FCF	0.341*** (0.120)	-0.086 (0.111)	-0.056 (0.350)	-0.242 (0.274)	0.090 (0.300)	0.255 (0.255)
Leverage	-0.170*** (0.039)	-0.071 (0.054)	1.021*** (0.095)	0.672*** (0.109)	0.770*** (0.080)	0.758*** (0.099)
Size	0.141*** (0.008)	-0.000 (0.019)	-0.297*** (0.014)	-0.199*** (0.036)	-0.187*** (0.011)	-0.123*** (0.030)
Profitability	0.135 (0.102)	0.002 (0.108)	-0.961*** (0.247)	-0.849*** (0.172)	-0.735*** (0.184)	-0.829*** (0.168)
CashHoldings	0.087 (0.062)	0.114 (0.070)	-0.155 (0.159)	-0.258* (0.144)	-0.108 (0.124)	-0.148 (0.130)
Tangibility	-0.032 (0.059)	0.236** (0.117)	0.073 (0.131)	-0.466** (0.204)	0.012 (0.089)	-0.130 (0.189)
TobinsQ	0.042*** (0.006)	0.009 (0.006)	-0.099*** (0.014)	-0.076*** (0.012)	-0.079*** (0.010)	-0.023* (0.012)
StockVolatility	-0.040*** (0.001)	-0.036*** (0.001)	0.017*** (0.001)	0.008*** (0.001)	0.012*** (0.001)	0.007*** (0.001)
_cons	3.183*** (0.179)	4.733*** (0.280)	8.922*** (0.322)	7.855*** (0.577)	8.227*** (0.208)	6.961*** (0.502)
Industry FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Method	POLS	FE	POLS	FE	POLS	FE
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	16028	16028	5238	5238	4230	4230
Adj/Within R^2	0.765	0.641	0.689	0.232	0.686	0.426

*Standard errors clustered at the firm level reported next to each coefficient. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 10: Lagged Hedging Robustness

	(28) dist_default	(29) dist_default	(30) dist_default	(31) dist_default	(32) dist_default
Panel A: Distance to Default					
L_Hedgeoverall	0.003 (0.017)				
L_Iroverall		0.022 (0.017)			-0.013 (0.018)
L_FXoverall			0.046** (0.018)		0.039** (0.020)
L_Comdoverall				0.082*** (0.024)	0.076*** (0.025)
Leverage	-0.109*** (0.040)	-0.114*** (0.041)	-0.112*** (0.040)	-0.115*** (0.040)	-0.114*** (0.040)
Size	0.135*** (0.008)	0.133*** (0.008)	0.130*** (0.008)	0.131*** (0.008)	0.128*** (0.008)
Profitability	-0.129** (0.063)	-0.135** (0.063)	-0.141** (0.063)	-0.134** (0.062)	-0.140** (0.062)
CashHoldings	0.070 (0.065)	0.073 (0.065)	0.068 (0.065)	0.079 (0.065)	0.075 (0.065)
Tangibility	0.009 (0.058)	0.008 (0.058)	0.015 (0.058)	-0.008 (0.058)	-0.000 (0.058)
TobinsQ	0.044*** (0.007)	0.044*** (0.007)	0.045*** (0.007)	0.045*** (0.006)	0.045*** (0.006)
StockVolatility	-0.042*** (0.001)	-0.042*** (0.001)	-0.042*** (0.001)	-0.042*** (0.001)	-0.042*** (0.001)
_cons	3.116*** (0.172)	3.125*** (0.171)	3.151*** (0.169)	3.147*** (0.175)	3.170*** (0.173)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	13675	13675	13675	13675	13675
Adj/Within R²	0.768	0.768	0.768	0.769	0.769
	Ln_CDS	*Ln_CDS*	*Ln_CDS*	*Ln_CDS*	*Ln_CDS*
Panel B: Ln(CDS Spread)					
L_Hedgeoverall	0.012 (0.032)				
L_Iroverall		-0.019 (0.028)			-0.004 (0.035)
L_FXoverall			-0.023 (0.035)		-0.010 (0.044)
L_Comdoverall				-0.041 (0.033)	-0.037 (0.035)
Leverage	1.035*** (0.099)	1.037*** (0.099)	1.036*** (0.099)	1.040*** (0.099)	1.040*** (0.099)
Size	-0.295*** (0.014)	-0.294*** (0.015)	-0.293*** (0.015)	-0.294*** (0.015)	-0.293*** (0.015)
Profitability	-1.386*** (0.220)	-1.379*** (0.219)	-1.383*** (0.220)	-1.394*** (0.220)	-1.391*** (0.219)
CashHoldings	-0.190 (0.167)	-0.184 (0.167)	-0.179 (0.167)	-0.201 (0.167)	-0.196 (0.167)
Tangibility	0.159 (0.145)	0.158 (0.145)	0.155 (0.145)	0.169 (0.145)	0.166 (0.146)
TobinsQ	-0.104*** (0.013)	-0.105*** (0.014)	-0.105*** (0.013)	-0.105*** (0.013)	-0.105*** (0.013)
StockVolatility	0.017*** (0.001)	0.017*** (0.001)	0.017*** (0.001)	0.017*** (0.001)	0.017*** (0.001)
_cons	8.893*** (0.280)	8.894*** (0.280)	8.889*** (0.280)	8.919*** (0.280)	8.914*** (0.279)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	4646	4646	4646	4646	4646
Adj/Within R²	0.677	0.677	0.677	0.678	0.678
	Ln_OAS	*Ln_OAS*	*Ln_OAS*	*Ln_OAS*	*Ln_OAS*
Panel C: Ln(OAS Spread)					
L_Hedgeoverall	0.021 (0.026)				
L_Iroverall		0.024 (0.022)			0.034 (0.028)
L_FXoverall			0.007 (0.026)		-0.010 (0.033)
L_Comdoverall				-0.011 (0.024)	-0.018 (0.025)
Leverage	0.789*** (0.083)	0.788*** (0.083)	0.790*** (0.083)	0.792*** (0.083)	0.789*** (0.083)
Size	-0.185*** (0.011)	-0.186*** (0.011)	-0.185*** (0.011)	-0.184*** (0.011)	-0.185*** (0.011)
Profitability	-1.208*** (0.154)	-1.211*** (0.153)	-1.203*** (0.153)	-1.207*** (0.153)	-1.220*** (0.153)
CashHoldings	-0.126 (0.130)	-0.123 (0.130)	-0.123 (0.130)	-0.127 (0.130)	-0.130 (0.130)
Tangibility	0.072 (0.089)	0.074 (0.089)	0.074 (0.089)	0.076 (0.089)	0.078 (0.090)
TobinsQ	-0.079*** (0.009)	-0.078*** (0.009)	-0.079*** (0.009)	-0.079*** (0.009)	-0.078*** (0.009)
StockVolatility	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)
_cons	8.411*** (0.212)	8.419*** (0.212)	8.412*** (0.212)	8.409*** (0.212)	8.419*** (0.212)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	3853	3853	3853	3853	3853
Adj/Within R²	0.679	0.679	0.679	0.679	0.679

*Standard errors clustered at the firm level reported next to each coefficient. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 11: PSM with Lagged Firm Controls

Outcome	N treated	N control pool	ATT	SE	t-stat	p-value
Panel A: Hedgeoverall (any hedging)						
dist_default	8695	4432	0.0641**	0.0294	2.178	0.0294
Ln_CDS	3546	1008	0.0393	0.0339	1.157	0.2472
Ln_OAS	2996	774	-0.0306	0.0266	-1.149	0.2507
Panel B: FXoverall (FX hedging)						
dist_default	6671	6449	0.1506***	0.0288	5.224	0.0000
Ln_CDS	2965	1522	-0.1144***	0.0310	-3.689	0.0002
Ln_OAS	2608	1168	-0.0163	0.0268	-0.607	0.5442
Panel C: Iroverall (IR hedging)						
dist_default	7413	5741	0.0671**	0.0297	2.260	0.0238
Ln_CDS	3189	1366	-0.0904***	0.0323	-2.801	0.0051
Ln_OAS	2704	1060	-0.0220	0.0222	-0.989	0.3225
Panel D: Comdoverall (commodity hedging)						
dist_default	2651	10500	0.1704***	0.0347	4.906	0.0000
Ln_CDS	1448	3109	-0.1350***	0.0355	-3.799	0.0001
Ln_OAS	1270	2464	-0.0599**	0.0252	-2.372	0.0177

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

Appendix

Appendix A: Multicollinearity Diagnostics (Variance Inflation Factors)

	VIF	*Tolerance (1/VIF)*
Panel A: Distance to Default sample (N = 16,110)		
Hedgeoverall	3.318	0.301
Iroverall	2.781	0.360
FXoverall	2.262	0.442
Comdoverall	1.234	0.811
Leverage	1.089	0.918
Size	1.541	0.649
Profitability	1.747	0.572
CashHoldings	1.642	0.609
Tangibility	1.227	0.815
TobinsQ	1.217	0.822
StockVolatility	1.577	0.634
Mean VIF	**1.785**	
Panel B: Ln(CDS Spread) sample (N = 5,242)		
Hedgeoverall	3.600	0.278
Iroverall	2.826	0.354
FXoverall	2.440	0.410
Comdoverall	1.226	0.816
Leverage	1.150	0.869
Size	1.194	0.837
Profitability	1.505	0.665
CashHoldings	1.266	0.790
Tangibility	1.342	0.745
TobinsQ	1.556	0.643
StockVolatility	1.382	0.723
Mean VIF	**1.772**	
Panel C: Ln(OAS Spread) sample (N = 4,236)		
Hedgeoverall	3.559	0.281
Iroverall	2.710	0.369
FXoverall	2.467	0.405
Comdoverall	1.232	0.812
Leverage	1.109	0.902
Size	1.186	0.843
Profitability	1.446	0.692
CashHoldings	1.270	0.787
Tangibility	1.302	0.768
TobinsQ	1.513	0.661
StockVolatility	1.335	0.749
Mean VIF	**1.739**	

Industry and year fixed effects are excluded from the VIF computations

Appendix B: White's Test for Heteroskedasticity

Statistic	*Value*	*Note*
Panel A: Distance to Default sample		
Observations	16,110	
Chi-squared statistic	6,956.498	df = 73
p-value	**< 0.001**	*Reject H_0: heteroskedasticity present*
Panel B: Ln(CDS Spread) sample		
Observations	5,242	
Chi-squared statistic	423.140	df = 73
p-value	**< 0.001**	*Reject H_0: heteroskedasticity present*
Panel C: Ln(OAS Spread) sample		
Observations	4,236	
Chi-squared statistic	165.566	df = 73
p-value	**< 0.001**	*Reject H_0: heteroskedasticity present*

White's (1980) general test for heteroskedasticity. Null hypothesis: error variance is constant (homoskedasticity).

Appendix C: Hausman Test (Fixed Effects vs Random Effects)

Statistic	*Value*	*Note*
Panel A: Distance to Default sample		
Observations	16,110	Firms = 2,923
Chi-squared statistic	406.342	df = 21
p-value	**< 0.001**	*Reject H_0: Fixed Effects preferred*
Panel B: Ln(CDS Spread) sample		
Observations	5,242	Firms = 822
Chi-squared statistic	361.668	df = 21
p-value	**< 0.001**	*Reject H_0: Fixed Effects preferred*
Panel C: Ln(OAS Spread) sample		
Observations	4,236	Firms = 549
Chi-squared statistic	216.496	df = 21
p-value	**< 0.001**	*Reject H_0: Fixed Effects preferred*

Appendix D: Regression model excluding and lagging stock volatility

Panel A: Excluding Stock Volatility					
	(1a)	*(2a)*	*(3a)*	*(4a)*	*(5a)*
	dist_default	*dist_default*	*dist_default*	*dist_default*	*dist_default*
Hedgeoverall	0.095*** (0.027)				
Iroverall		0.124*** (0.026)			0.042 (0.029)
FXoverall			0.163*** (0.030)		0.117*** (0.033)
Comdoverall				0.158*** (0.039)	0.111*** (0.040)
Leverage	-0.817*** (0.064)	-0.828*** (0.064)	-0.808*** (0.064)	-0.810*** (0.063)	-0.820*** (0.064)
Size	0.301*** (0.011)	0.298*** (0.011)	0.291*** (0.011)	0.302*** (0.011)	0.287*** (0.011)
Profitability	1.618*** (0.089)	1.605*** (0.089)	1.597*** (0.088)	1.630*** (0.089)	1.590*** (0.088)
CashHoldings	-0.383*** (0.092)	-0.366*** (0.091)	-0.385*** (0.091)	-0.371*** (0.091)	-0.370*** (0.091)
Tangibility	-0.374*** (0.097)	-0.372*** (0.096)	-0.345*** (0.097)	-0.398*** (0.097)	-0.374*** (0.097)
TobinsQ	0.100*** (0.010)	0.101*** (0.010)	0.101*** (0.010)	0.101*** (0.010)	0.102*** (0.010)
_cons	0.102 (0.282)	0.125 (0.282)	0.202 (0.278)	0.122 (0.289)	0.237 (0.287)
Stock Volatility	Excluded	Excluded	Excluded	Excluded	Excluded
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	16,110	16,110	16,110	16,110	16,110
Adj R²	0.508	0.508	0.509	0.508	0.510
Panel B: Lagged Stock Volatility (t−1)					
	(1b)	*(2b)*	*(3b)*	*(4b)*	*(5b)*
	dist_default	*dist_default*	*dist_default*	*dist_default*	*dist_default*
Hedgeoverall	0.036 (0.023)				
Iroverall		0.063*** (0.022)			0.017 (0.024)
FXoverall			0.080*** (0.024)		0.051* (0.027)
Comdoverall				0.122*** (0.031)	0.103*** (0.032)
Leverage	-0.556*** (0.054)	-0.564*** (0.054)	-0.555*** (0.053)	-0.557*** (0.053)	-0.563*** (0.054)
Size	0.198*** (0.010)	0.195*** (0.010)	0.192*** (0.010)	0.195*** (0.010)	0.189*** (0.010)
Profitability	0.963*** (0.080)	0.953*** (0.079)	0.952*** (0.079)	0.964*** (0.079)	0.948*** (0.079)
CashHoldings	-0.088 (0.084)	-0.079 (0.084)	-0.091 (0.084)	-0.075 (0.084)	-0.078 (0.084)
Tangibility	-0.182** (0.075)	-0.182** (0.075)	-0.169** (0.075)	-0.206*** (0.075)	-0.196*** (0.075)
TobinsQ	0.080*** (0.009)	0.080*** (0.009)	0.080*** (0.009)	0.080*** (0.009)	0.081*** (0.009)
L_StockVolatility	-0.023*** (0.001)	-0.023*** (0.001)	-0.023*** (0.001)	-0.023*** (0.001)	-0.023*** (0.001)
_cons	1.839*** (0.224)	1.851*** (0.225)	1.887*** (0.221)	1.887*** (0.229)	1.924*** (0.227)
Stock Volatility	Lagged (t-1)	Lagged (t-1)	Lagged (t-1)	Lagged (t-1)	Lagged (t-1)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	13,187	13,187	13,187	13,187	13,187
Adj R²	0.577	0.578	0.578	0.578	0.579

Standard errors clustered at the firm level reported next to each coefficient in parentheses. Panel A: Excluding stock volatility. Panel B: Lagged stock volatility (t-1)
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Appendix E: PSM Hedging initiation and suspension (Year on Year)

Outcome	Event	N	ATT (SE)	p-value
Panel A: Hedgeoverall (any hedging)				
dist_default	Init.	678	-0.0847 (0.0540)	0.1166
dist_default	Susp.	638	-0.1247** (0.0515)	0.0154
Ln_CDS	Init.	166	0.0178 (0.0604)	0.7679
Ln_CDS	Susp.	165	-0.1091* (0.0608)	0.0729
Ln_OAS	Init.	138	0.0648 (0.0747)	0.3854
Ln_OAS	Susp.	107	-0.0036 (0.0603)	0.9527
Panel B: FXoverall (FX hedging)				
dist_default	Init.	576	-0.0511 (0.0552)	0.3552
dist_default	Susp.	545	-0.0624 (0.0591)	0.2907
Ln_CDS	Init.	157	-0.0186 (0.0584)	0.7500
Ln_CDS	Susp.	151	-0.0107 (0.0539)	0.8429
Panel C: Iroverall (IR hedging)				
dist_default	Init.	902	-0.0171 (0.0486)	0.7247
Ln_CDS	Susp.	242	-0.0365 (0.0436)	0.4020
Ln_OAS	Init.	192	-0.0147 (0.0438)	0.7381
Ln_OAS	Susp.	171	0.1168*** (0.0416)	0.0050
Panel D: Comdoverall (commodity hedging)				
dist_default	Init.	353	-0.0554 (0.0810)	0.4938
dist_default	Susp.	366	-0.0542 (0.0887)	0.5415
Ln_CDS	Init.	168	-0.0563 (0.0504)	0.2633
Ln_CDS	Susp.	152	0.0020 (0.0613)	0.9742
Ln_OAS	Init.	144	-0.0332 (0.0517)	0.5208
Ln_OAS	Susp.	129	-0.0509 (0.0481)	0.2905

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

Appendix F: Robustness model excluding profitability

	(22)	(22a)
	dist_default	*dist_default*
	From Table 9	(2) No Profitability
Hedgeoverall	0.027 (0.017)	0.027 (0.017)
FCF_TA	-0.554*** (0.117)	-0.423*** (0.073)
Hedge_x_FCF	0.341*** (0.120)	0.327*** (0.118)
Leverage	-0.170*** (0.039)	-0.163*** (0.039)
Size	0.141*** (0.008)	0.141*** (0.008)
Profitability	0.135 (0.102)	
CashHoldings	0.087 (0.062)	0.068 (0.061)
Tangibility	-0.032 (0.059)	-0.016 (0.058)
TobinsQ	0.042*** (0.006)	0.042*** (0.006)
StockVolatility	-0.040*** (0.001)	-0.041*** (0.001)
_cons	3.183*** (0.179)	3.189*** (0.178)
Profitability control	Included	Excluded
Industry FE	Yes	Yes
Year FE	Yes	Yes
Method	POLS	POLS
Standard Errors	Clustered	Clustered
Observations	16,028	16,044
Adj R-squared	0.765	0.765

Standard errors clustered at the firm level in parentheses.

** p < 0.10, ** p < 0.05, *** p < 0.01.*

Appendix G: Robustness Hedging and default risk (explanatory variables t-1)

	(28a)	(29a)	(30a)	(31a)	(32a)
	dist default	*dist default*	*dist default*	*dist default*	*dist default*
Panel A: Distance to Default					
L_Hedgeoverall	0.015 (0.023)				
L_Iroverall		0.049** (0.022)			0.013 (0.025)
L_FXoverall			0.064*** (0.024)		0.043 (0.027)
L_Comdoverall				0.088*** (0.033)	0.073** (0.034)
L_Leverage	-0.398*** (0.054)	-0.408*** (0.054)	-0.400*** (0.053)	-0.401*** (0.053)	-0.407*** (0.054)
L_Size	0.200*** (0.010)	0.197*** (0.010)	0.194*** (0.010)	0.197*** (0.010)	0.192*** (0.010)
L_Profitability	0.986*** (0.080)	0.976*** (0.080)	0.974*** (0.079)	0.985*** (0.079)	0.972*** (0.079)
L_CashHoldings	0.144* (0.080)	0.149* (0.079)	0.140* (0.079)	0.153* (0.079)	0.150* (0.079)
L_Tangibility	-0.194** (0.076)	-0.195** (0.076)	-0.185** (0.076)	-0.212*** (0.077)	-0.204*** (0.077)
L_TobinsQ	0.050*** (0.008)	0.051*** (0.008)	0.051*** (0.008)	0.051*** (0.008)	0.051*** (0.008)
L_StockVolatility	-0.024*** (0.001)	-0.024*** (0.001)	-0.024*** (0.001)	-0.024*** (0.001)	-0.024*** (0.001)
Constant	0.861*** (0.158)	0.885*** (0.158)	0.917*** (0.159)	0.897*** (0.158)	0.941*** (0.160)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	13183	13183	13183	13183	13183
Adj. R-squared	0.564	0.564	0.564	0.564	0.565
	(1)	(2)	(3)	(4)	(5)
	Ln CDS	*Ln CDS*	*Ln CDS*	*Ln CDS*	*Ln CDS*
Panel B: Ln(CDS Spread)					
L_Hedgeoverall	0.014 (0.034)				
L_Iroverall		-0.014 (0.029)			0.002 (0.037)
L_FXoverall			-0.023 (0.037)		-0.017 (0.047)
L_Comdoverall				-0.033 (0.035)	-0.029 (0.037)
L_Leverage	1.041*** (0.102)	1.043*** (0.102)	1.041*** (0.102)	1.045*** (0.102)	1.044*** (0.102)
L_Size	-0.309*** (0.015)	-0.308*** (0.015)	-0.307*** (0.015)	-0.308*** (0.015)	-0.306*** (0.015)
L_Profitability	-1.448*** (0.230)	-1.442*** (0.230)	-1.446*** (0.231)	-1.452*** (0.230)	-1.452*** (0.230)
L_CashHoldings	-0.187 (0.167)	-0.182 (0.168)	-0.177 (0.167)	-0.194 (0.167)	-0.188 (0.167)
L_Tangibility	0.210 (0.147)	0.209 (0.147)	0.205 (0.147)	0.217 (0.147)	0.213 (0.147)
L_TobinsQ	-0.110*** (0.014)	-0.111*** (0.014)	-0.111*** (0.014)	-0.111*** (0.014)	-0.111*** (0.014)
L_StockVolatility	0.014*** (0.001)	0.014*** (0.001)	0.014*** (0.001)	0.014*** (0.001)	0.014*** (0.001)
Constant	9.239*** (0.284)	9.235*** (0.285)	9.228*** (0.284)	9.237*** (0.285)	9.230*** (0.284)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	4589	4589	4589	4589	4589
Adj. R-squared	0.635	0.635	0.635	0.636	0.635
	(1)	(2)	(3)	(4)	(5)
	Ln OAS	*Ln OAS*	*Ln OAS*	*Ln OAS*	*Ln OAS*
Panel C: Ln(OAS Spread)					
L_Hedgeoverall	0.020 (0.028)				
L_Iroverall		0.019 (0.024)			0.031 (0.031)
L_FXoverall			0.000 (0.028)		-0.018 (0.036)
L_Comdoverall				-0.004 (0.025)	-0.008 (0.027)
L_Leverage	0.698*** (0.082)	0.697*** (0.082)	0.699*** (0.082)	0.700*** (0.082)	0.696*** (0.082)
L_Size	-0.199*** (0.011)	-0.199*** (0.011)	-0.198*** (0.011)	-0.198*** (0.011)	-0.198*** (0.011)
L_Profitability	-1.007*** (0.158)	-1.010*** (0.158)	-1.004*** (0.157)	-1.006*** (0.158)	-1.017*** (0.158)
L_CashHoldings	-0.129 (0.139)	-0.127 (0.139)	-0.125 (0.138)	-0.127 (0.139)	-0.128 (0.139)
L_Tangibility	0.076 (0.094)	0.078 (0.094)	0.076 (0.094)	0.078 (0.094)	0.078 (0.095)
L_TobinsQ	-0.096*** (0.011)	-0.096*** (0.011)	-0.097*** (0.011)	-0.097*** (0.011)	-0.096*** (0.011)
L_StockVolatility	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)
Constant	8.068*** (0.201)	8.074*** (0.200)	8.071*** (0.200)	8.071*** (0.200)	8.068*** (0.200)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Method	POLS	POLS	POLS	POLS	POLS
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	3818	3818	3818	3818	3818
Adj. R-squared	0.628	0.628	0.628	0.628	0.628

*Standard errors clustered at the firm level reported next to each coefficient. Panel A: Distance to default. Panel B: CDS spread. Panel C: OAS spread. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Appendix H: Hedging identification approach

Here follows a detailed breakdown of our hedging classification method. To start, a list of all Russell 3000 constituents at the end of each calendar year is retrieved from Bloomberg for the years 2014-2024. From Bloomberg, the central index key (CIK) is also retrieved, which is a number that is used to access a firm's specific filing from the Securities and Exchange Commission's EDGAR database, where each company's 10-K filing is stored. All CIK numbers are formatted and stored in a comma-separated-values (CSV) file, which the Python model is then able to read.

The model retrieves the CIK number for each index constituent and then accesses each company's filing using the Edgartools package. The full filing is retrieved from the EDGAR database, and the textual analysis can then begin. Our model employs several classification strategies to ensure it is as accurate as possible. First, a regular expression (Regex) search is utilized to localize a combination of keywords in the text that might indicate derivative hedging use. A full list of the keywords employed for this first step is provided in Appendix I. The model saves 800 characters before and after the identified keywords and then divides them into sentences, which makes further interpretation and auditing easier.

After possible hedging segments are identified, we employ SpaCY, which is a rule-based natural language processing (NLP). It analyzes the segments to verify that it is actual hedging through derivatives that the company is doing, and not only mentioning the instruments or certain legislations. For example, "We do not hedge commodity exposure using derivatives" still contains hedge, commodity, hedging, and derivatives, but explicitly states that they do not use them. SpaCy is a rule-based natural language processing classifier and will only assign a positive value to the dummy variable if the word indicating hedging is either closely followed by or before another word that mentions explicit use of the instrument. This reduces false positives.

Because the binary derivative classification is the principal explanatory variable, we also classify the hedged risk into three categories: interest rate (IR), foreign exchange (FX), and commodity. For each category, a dedicated spaCy matcher requires a category-specific word (for FX, terms such as foreign, currency, exchange, or specific currency names; for IR, terms such as interest, rate; for commodity, terms such as commodity, fuel, oil, or natural gas; Appendix I) to appear within a short span of the "hedge".

As a robustness towards this classification, we employ BART, a pretrained machine learning model developed by Facebook AI, which is usable in Python (Lewis et al. 2019). It is able to do a zero-shot classification if a firm is hedging or not. BART looks at the possible hedging segment and then assigns one of two labels. In the overall hedging case, "This text describes a company using derivatives to hedge risk" or "This text discusses derivatives or risk management but does not describe using derivatives to hedge risk." Bart assigns a score between 0 and 1 for the probability it assigns each label to each text segment. If SpaCY marks a segment as evidence of hedging, then BART is used to verify that SpaCY identified it correctly, and we set a threshold of 0.75 for it to be verified by BART. If SpaCY does not assign hedging to a text segment identified by the Regex, then BART is also employed, and it is able to assign hedging to a firm-year observation anyway if it deems that the text segment describes hedging with derivatives with a high enough probability. In our case, we set this threshold high to 0.9 to minimize the number of false positives. This means that BART is employed as a robustness measure to identify hedging in those cases where the rule-based classifier missed it, for example, if the wording is ambiguous.

To validate our model and the identification of hedging behavior, we employ a manual audit of 100 of the firm's annual reports randomly selected from the final model's output. We make sure to extract audit samples from all hedging categories. The audit is performed by one of the authors unknowingly of the actual output from the model. In Appendix J, we present an example of how the manual audit was coded for the first 10 firms in the audited sample. We also provide confusion matrices and performance metrics for each hedging category (Overall, FX, IR, Commodity). The overall agreement rate between our own manual audit and the model is 90%, with a low of 85% for the IR hedging indicator and a high of 93% for commodity hedging. Overall, the model has more false positives than false negatives. While these results tell us that the model does not perfectly classify hedging and non-hedging behavior, we believe that our audit process confirms that the results from the model can be viewed as good enough for the scope of our study. Considering that the automated approach allows us to collect hedging data for a far wider set of companies than would have been possible under only manual classification, we believe that the tradeoff between accuracy and quantity has been worth it for the study.

Appendix I: Hedging keywords

Component	Terms
Use / action verbs	use, used, using, utilise/utilize (and -d), enter into, entering into, entered into, execute, executed, executing, designate, designated
Derivative instruments	derivative(s), derivative instrument(s), derivative financial instrument(s), swap(s), forward(s), future(s), option(s)
Hedging / risk terms	hedge, hedging, to hedge, risk management, manage exposure
Hedge-accounting designations	cash flow hedge(s), fair value hedge(s), net investment hedge(s), accounting hedge(s), designated / not designated as accounting hedge
FX exposure terms	foreign currency forward contract(s), foreign exchange contract(s)
IR exposure terms	interest rate(s), LIBOR, SOFR, floating-rate, fixed-rate, variable-rate, basis swap, rate swap, interest expense, senior notes, debt, treasury lock
Commodity exposure terms	commodity / commodities, commodity price / risk / exposure, crude oil, natural gas, oil price(s), energy price / cost / risk, fuel cost / price / risk, raw material cost, input cost

Appendix J: Example of audit process

company	fyear	Overall	FX	IR	COMD	Overall	FX	IR	COMD
ACUMEN PHARMACEUTICALS INC	2024	1	0	1	0	1	0	1	0
ARGAN INC	2017	1	1	0	0	0	0	0	0
APOGEE ENTERPRISES INC	2024	1	1	1	1	1	1	1	1
ADVANSIX INC	2023	1	1	0	0	1	1	1	0
AIR TRANSPORT SERVICES GROUP	2017	1	1	1	0	1	0	1	0
AZENTA INC	2015	1	1	1	0	1	1	0	0
CAREMAX INC	2020	0	0	0	0	0	0	0	0
CORTEVA INC	2020	1	1	1	1	1	1	0	1
VAALCO ENERGY INC	2021	1	0	0	1	1	0	0	1
ENERSYS	2024	1	1	1	1	1	1	1	1

Where the white fields are from the Python model's output and the yellow fields are from the manual audit.

Appendix K: Confusion Matrices

Overall hedging

	Model = 1	Model = 0	Total
Human = 1	70	2	72
Human = 0	8	20	28
Total	78	22	100

Metric	Overall
Agreement rate	90.0%
False-positive rate	28.6%
False-negative rate	2.8%
N	100

Confusion matrix FX

	Model = 1	Model = 0	Total
Human = 1	51	1	52
Human = 0	10	38	48
Total	61	39	100

Metric	FX
Agreement rate	89.0%
False-positive rate	20.8%
False-negative rate	1.9%
N	100

Confusion matrix IR

	Model = 1	Model = 0	Total
Human = 1	50	2	52
Human = 0	13	35	48
Total	63	37	100

Metric	IR
Agreement rate	85.0%
False-positive rate	27.1%
False-negative rate	3.8%
N	100

Confusion matrix Commodity

	Model = 1	Model = 0	Total
Human = 1	34	1	35
Human = 0	6	59	65
Total	40	60	100

Metric	Commodity
Agreement rate	93.0%
False-positive rate	9.2%
False-negative rate	2.9%
N	100

Appendix L: Summary statistics before transformation

	N	Mean	Median	SD	Min	Max
Panel A: Dependent Variables and Hedging Dummies						
Distance to default	16,205	2.805	2.617	1.298	-1.292	6.604
Ln_CDS	5,431	4.843	4.718	0.965	2.917	7.253
Ln_OAS	4,281	5.125	5.087	0.665	2.099	8.461
Hedging Dummy	21,508	0.544	1.000	0.498	0.000	1.000
FX Hedging Dummy	21,508	0.403	0.000	0.490	0.000	1.000
IR Hedging Dummy	21,508	0.441	0.000	0.497	0.000	1.000
Commodity Hedging Dummy	21,508	0.154	0.000	0.361	0.000	1.000
Panel B: Firm-Level Control Variables						
Leverage	21,484	0.294	0.265	0.274	0.000	7.480
Total Assets (Millions)	21,508	8611.174	1509.673	29804.768	0.150	624894.000
Profitability	21,398	0.032	0.095	0.301	-15.427	1.746
Cash Holdings	21,473	0.166	0.101	0.191	0.000	1.000
Tangibility	21,393	0.220	0.135	0.222	0.000	1.000
Tobin's Q	21,178	2.399	1.592	4.666	0.114	522.493
1-Year Stock Return Volatility (%)	20,228	46.913	40.028	25.994	0.407	289.335
Panel C: Interaction Moderators						
Foreign income share (%)	20,057	25.816	17.747	27.209	0.000	98.938
Interest Coverage	18,237	-40.368	7.131	3502.672	-253914.480	134338.500
Free Cash Flow / Total Assets	21,264	-0.003	0.040	0.176	-1.044	0.329
Commodity intensive sector dummy	21,508	0.121	0.000	0.326	0.000	1.000

This table reports summary statistics on the raw, pre-winsorization sample, to be compared against the winsorized statistics in Table 1.

Appendix M: Instrumental Variables Estimates (2SLS)

	(33) *dist default*
Hedgeoverall	1.261*** (0.395)
Leverage	-0.329*** (0.094)
Size	0.028 (0.035)
Profitability	-0.441*** (0.128)
CashHoldings	0.040 (0.094)
Tangibility	-0.086 (0.091)
TobinsQ	0.064*** (0.011)
StockVolatility	-0.040*** (0.001)
Observations	13,663
Industry FE	Yes
Year FE	Yes
Standard Errors	Clustered
Method	2SLS
Kleibergen-Paap F Statistics	21.517

Standard errors clustered at the firm level reported next to each coefficient in parentheses.
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Appendix N: AI Statement

Tools:

- Claude by Anthropic
- ChatGPT by OpenAI
- Grammarly by Superhuman Platform Inc.
- NotebookLM by Google

Use of AI:

For this study, ChatGPT has assisted in finding relevant research articles within the thesis topic and that grammar, spelling, and table references are correct. Grammarly has also been used for general spell and grammar checks as well as for finding relevant synonyms. Claude has been used to generate parts of the commands in STATA, handle the data, and help with the code for the tables. Furthermore, it has been used to troubleshoot the Python model as well as generating some parts of the code. NotebookLM has been used to identify useful segments within research papers.