When Nature Makes the News: Biodiversity Shocks, Credit Risk, and Debt Discipline

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Abstract

This paper examines how U.S. non-financial firms adjust credit risk and financing structures in association with biodiversity-related news shocks, comparing the Aichi period (2006–2020) with the post-Aichi period (2021–2023). During the Aichi period, negative biodiversity shocks were correlated with higher default risk, increased equity volatility, and wider credit spreads, but these effects did not differ systematically between high- and low-risk firms. In the post-Aichi period, however, clear divergences emerge. Low-risk firms deleverage strategically and accumulate precautionary raw material inventories, thereby strengthening liquidity positions and signaling prudence to creditors. By contrast, high-risk firms, concentrated in resource-intensive sectors, face rising operating costs and remain dependent on external finance. Unable to deleverage, they substitute long-term with short-term debt, exposing themselves to higher liquidity pressure. Creditors respond by moderating overall spreads but imposing maturity shortening, a debt-disciplining mechanism that constrains excess risk-taking. Equity markets appear to recognize this discipline, penalizing high-risk firms less harshly than before, though the benefits remain limited compared to low-risk peers. Overall, the relative penalty for high-risk firms increases by about 18 basis points in the post-Aichi period, underscoring how biodiversity shocks interact with regulatory pressures to widen the credit risk gap between high- and low-exposure firms.

Keywords: Biodiversity Risk, Credit Risk, Aichi Targets, Maturity Shortening, Debt Disciplining, Credit Spreads

Introduction

Over the past decade, policymakers, investors, and researchers have advanced from diagnosing climate risk to establishing a well-developed field of climate finance (Giglio et al. (2021); Stroebel and Wurgler (2021); Hong et al. (2020)). Biodiversity finance, by contrast, remains underdeveloped. This gap is problematic since biodiversity risks are interlinked with climate change and are increasingly shown to be financially material (Giglio et al., 2023). Biodiversity loss generates physical risks through declining ecosystem services such as water availability, soil fertility, and pollination, which disrupt production and propagate through supply chains. It also creates transition risks through regulations, disclosure requirements, liability rules, procurement standards, and changing consumer demand, all of which affect costs, business models, and the pricing of capital. The extent to which firms depend on and are vulnerable to these biodiversity-related physical and transition risks could be referred to as biodiversity risk exposure.

Existing empirical work has largely examined climate-related physical and transition risks (e.g., Seltzer et al. (2022); Ilhan et al. (2021); Faralli and Tomaselli (2024); Martini et al. (2024)). In contrast, the consequences of biodiversity exposure related risks remain comparatively unexplored. Recent studies have begun to address this gap by quantifying biodiversity risk (Giglio et al. (2023)) and showing that lenders price it, as more exposed borrowers face higher loan spreads (Deng and Lin (2025); Becker et al. (2025)).

Giglio et al. (2023) construct an aggregate news-based index of biodiversity risk and firm-level exposure metrics derived from 10-K text and a large survey of finance professionals, and show that biodiversity risk is distinct from climate risk and priced in equities. On bank lending, multiple studies document that lenders price nature-related risk: Becker et al. (2025) link borrowers' biodiversity exposure to higher spreads in EU/UK syndicated loans; Deng and Lin (2025) find that U.S. borrowers with greater biodiversity risk pay higher loan spreads, with heterogeneity between "regulatory" (perpetrator) and "physical" (victim) channels; and Canipek et al. (2024) show for U.S. syndicated loans that greater firm dependence on ecosystem services raises spreads, quantifying the effect at roughly 0.2–0.3% per 1% increase in nature dependency.

Complementing these cross-sectional findings, Li and Naffa (2025) exploit the Kunming Declaration as an exogenous policy shock to causally identify higher loan pricing for nature-exposed firms, while policy work by the NGFS (2023) provides the supervisory rationale for how such risks transmit into bank balance sheets. The emerging literature measures biodiversity exposure using news-based indices, text-based measures from 10-K filings and corporate disclosures, survey-based assessments, and input-dependence ("nature dependency") metrics, and typically estimates pricing effects with loan-level data in difference-in-differences settings around disclosure or policy shocks. Nonetheless, important gaps remain, particularly regarding how biodiversity risks affect the broader financing structures and credit risk of firms beyond adjustments in loan spreads.

In this thesis, I aim to answer the following question: "How are the credit risk, financing conditions and leverage of non-bank U.S. firms associated with biodiversity-related news shocks?" To address this, I study publicly traded NASDAQ firms and adopt a descriptive approach to examine patterns in firms' credit risk and balance sheet adjustments during periods of heightened transitional risk. While the results cannot fully disentangle whether observed changes reflect firm-side decisions (demand) or creditor-imposed constraints (supply), they document the joint dynamics of borrowers and lenders in connection with biodiversity exposure. I distinguish between two periods: the pre-Aichi phase (2006–2020) and the post-Aichi phase (2021–2023). The Aichi Biodiversity Targets, adopted in 2010 under the Convention on Biological Diversity, set 20 global goals to halt biodiversity loss by 2020, yet none were fully achieved, leaving global biodiversity decline largely unabated. Following their expiry, biodiversity regulation entered a more stringent phase, characterized by the EU Biodiversity Strategy for 2030, the proposed Nature Restoration Law, mandatory disclosure requirements such as the Corporate Sustainability Reporting Directive (CSRD), and the launch of the Taskforce on Nature-related Financial Disclosures (TNFD). At the global level, the Kunming–Montreal Global Biodiversity Framework (2022) introduced binding conservation and restoration commitments. These regulatory shifts, coupled with intensified supervisory scrutiny, have amplified transitional risks, raising compliance costs and increasing pressure on firms with significant biodiversity dependencies.

An immediate question arises in this context. Who cares about credit risk? In the loan pricing literature, credit risk is a key component of loan spreads. The standard reduced-form framework, following Jarrow and Turnbull (1995) and Duffie and Singleton (1999), expresses the credit spread as:

$$CreditSpread = -\frac{1}{T} \cdot \ln(1 - PD \cdot LGD) \tag{1}$$

where T is time to maturity, PD is the cumulative risk-neutral probability of default, and LGD refers to the loss given default. $LGD = EAD \cdot (1 - RR)$, with EAD being the exposure at default and RR being the recovery rate (Basel IRB Framework). In this decomposition, PD reflects firm fundamentals and market signals such as leverage, profitability, liquidity, equity returns, volatility, and distance-to-default (Shumway (2001); Hillegeist et al. (2004); Campbell et al. (2008)). LGD depends on capital structure and the business cycle, with recoveries lower in downturns and often positively correlated with PD (Altman et al. (2005); Frye (2000)). In practice, expected loss and capital charges are driven directly by PD and LGD. Holding recovery fixed at 40%[1]—a common simplification—any news-induced change in PD maps mechanically into credit spreads through the formula above. Negative news can reduce expected cash flows or increase their volatility, both of which raise default risk (Trueman and Titman (1988); Minton and Schrand (1999); Acharya et al. (2012)). Additionally, a shorter maturity (T) increases the spread because the same default risk is concentrated over a shorter horizon. Intuitively, lenders require higher annualized compensation when risk is realized sooner, while longer maturities spread the risk over time, reducing the per-period spread[2].

To proxy firms' default risk and financial health, I construct a risk-neutral probability of default (PD) measure based on balance sheet fundamentals such as capital structure, equity returns, and

[1]This means assuming Loss given Default, LGD is 60%

[2]A common simplification is also to assume that time to maturity is 1 year for computing 1-year credit spreads. I employ these assumptions to estimate the credit spreads from PD using equation 1.

return volatility. This follows the structural framework of Merton (1974) and its empirical adaptation by Afik et al. (2016). The empirical strategy involves a pre- versus post-Aichi regression analysis of quarterly changes in firm-level PDs and balance sheet fundamentals in response to negative biodiversity news shocks.

Findings for the Aichi period suggest that negative biodiversity news shocks were largely unanticipated, and firms reacted in line with intuition: probabilities of default increased, stock volatility rose, equity returns declined, and firms faced higher operating costs alongside reduced long-term borrowing and rising interest expenses. These patterns are consistent with evidence in Becker et al. (2025), highlighting how sudden news of biodiversity loss translated into higher perceived risk and tighter financing conditions. Importantly, divergences between high- and low-risk firms during this period remained economically small and statistically insignificant, suggesting that creditors had yet to differentiate strongly across biodiversity exposures.

In the post-Aichi period, however, I document a pronounced divergence between high- and low-risk firms. Both groups experience improvements in credit fundamentals (lower probabilities of default and volatility) but the improvements are smaller for high-risk firms, indicating that stricter regulation penalised them more heavily. Findings from the panel regression pooling firms across the pre- and post-Aichi periods indicate that, under standard assumptions, a one-standard-deviation biodiversity news shock widened the post-Aichi credit spread gap between high- and low-risk firms by 18 bps relative to the Aichi baseline. To put this into perspective, in U.S. investment-grade markets the spread difference between a BBB-rated and an A-rated borrower is typically 15–25 bps. The post-Aichi widening therefore implies that creditors treated high-risk firms as if they had lost roughly one notch of credit quality following the expiration of the Aichi Targets. At the same time, borrowing structures adjust sharply. Low-risk firms undergo strategic deleveraging, while high-risk firms increase their reliance on short-term borrowing, consistent with creditors shortening maturities to enforce closer monitoring (Ivanov et al., 2024). This maturity tightening creates liquidity pressure on high-risk firms, who must refinance more frequently under higher spreads.

The effects also extend to corporate operations. In the post-Aichi period, the cross-sectional gap in operating expenses as a reaction to biodiversity news shocks widens. Low-risk firms, benefiting from deleveraging and improved creditworthiness, are able to pre-emptively increase raw material stockpiling, whereas high-risk firms respond more cautiously, limiting inventory accumulation under tighter liquidity and shorter maturities. Credit markets interpret both adjustments as positive: deleveraging strengthens the balance sheets of low-risk firms, while creditor discipline improves the efficiency of high-risk firms. As a result, credit spreads decline for both groups, but the reduction is more pronounced for low-risk firms. This asymmetry leads to a significant widening of the relative spread gap by around 18 basis points between high- and low-risk firms from the Aichi to the post-Aichi period.

$$\underbrace{(\text{C.Spread}_{\text{H, Post}} - \text{C.Spread}_{\text{L, Post}})}_{\text{Relative Spread Gap Post-Aichi Period}} - \underbrace{(\text{C.Spread}_{\text{H, Pre}} - \text{C.Spread}_{\text{L, Pre}})}_{\text{Relative Spread Gap during Aichi Period}} = 18 \text{ bps} \qquad (2)$$

The remainder of this thesis is structured as follows: Section 2 outlines the data and methodology, including the construction of the proxy for firm health - Probability of Default. It introduces the data used for measuring biodiversity news shocks and biodiversity risk exposure and discusses the summary statistics of the variables used. Section 3 introduces the identification strategy and the empirical method I used for my analysis. In Section 4, I discuss the results of the analysis and Section 5 concludes by summarising the findings and acknowledging the shortcomings and scope for further analysis.

Data and Methodology

Data - Quarterly Firm Fundamentals and Bankruptcy

In my thesis, I employ the Compustat Capital IQ Fundamentals–Quarterly dataset covering the period from 2006Q1 to 2023Q4 as the primary source of firm-level data. The initial sample consists of 2,184 non-financial firms publicly traded on NASDAQ between January 2006 and December 2023. To compute equity returns and return volatility, I complement this with daily stock price data[3]. Observations with missing values or discontinued data points are dropped, reducing the final sample to 1,162 firms. The sample spans 22 sectors, excluding banks and other financial institutions, as defined by the GICS4 industry classification [4].

To estimate default probabilities within the Merton framework, I supplement firm-level data with bankruptcy records from the Bankruptcy Research Database (2022). This dataset provides comprehensive and up-to-date information on U.S. firms filing for bankruptcy under both Chapter 7 and Chapter 11, including the exact filing dates. [5]

Table C.1 summarizes the main variables. Firms are large on average, with mean market equity of USD 14.7 billion and total debt of USD 7.2 billion, though both exhibit wide dispersion. Risk

[3]Daily closing prices are adjusted for stock splits and dividends using the WRDS adjustment factor (`ajexdi`); returns are then computed from the first difference of the adjusted series.

[4]Table A.1 in the Appendix shows the number of companies under each industry.

[5]The annual number of defaulting firms from this dataset is reported in Table A.2.

measures show an average implied asset volatility of 0.049, a probability of default of 0.057, and log equity returns of 0.016. Log equity volatility averages –3.125, equivalent to a volatility of about 0.044[6].

Estimating Default Risk as a proxy for Firm Health

In this section, I discuss the construction of Merton-implied risk-neutral PDs, which serve as a proxy for firm health and an important input into the valuation of loan spreads. Merton (1974), building on Black and Scholes (1973), developed a structural model of default risk valuation in which equity is modeled as a call option on the firm's assets, reflecting the residual nature of shareholder claims once debt obligations are satisfied. Implementing this framework requires estimates of the firm's asset value, asset volatility, and expected asset return. Following Jones et al. (1984), Ronn and Verma (1986), and later applications such as Campbell et al. (2008), I use the standard equation-system approach to recover asset value and volatility from market observables, while treating the expected asset return as an independent parameter. The detailed methodology is presented in Appendix Part B.

My estimation strategy follows the empirical implementation of Afik et al. (2016). Consistent with their specification, I measure firm debt as the sum of short-term liabilities and 0.1 times long-term liabilities, under the assumption that long-term debt has limited but existent predictive power. I evaluate model performance using the area under the receiver operating characteristic curve (AUC), a standard measure of discriminatory power also employed by Afik et al. (2016). This adjustment improves classification performance, and with it my model attains an AUC of 96%, comparable to their results and indicative of strong discriminatory power. For the expected asset return, I assume the risk-free rate, in line with Afik et al. (2016), who show that this choice outperforms equity-based proxies in terms of predictive accuracy[7].

According to Figure 1, observations classified as bankrupt ("LIQ") receive a mean PD close to 1 under the Merton model. The next highest risk is assigned to financially distressed firms rated "D" by S&P, while the lowest PDs are observed for the financially strongest firms rated A+. This pattern supports the validity of the estimation. It is important to note, however, that risk-neutral PDs represent a lower bound of default risk, as physical probabilities incorporate the additional risk premium demanded by risk-averse investors. In such a case, the expected return on assets would exceed the risk-free rate, resulting in higher default probabilities. Nevertheless, risk-neutral PDs are widely accepted for valuation purposes and provide a suitable proxy for

[6] The level is obtained by exponentiating the log value: $\exp(-3.125) \approx 0.044$.

[7] The detailed grid-testing of the various hyperparameters are done and reported in Appendix Table B.1

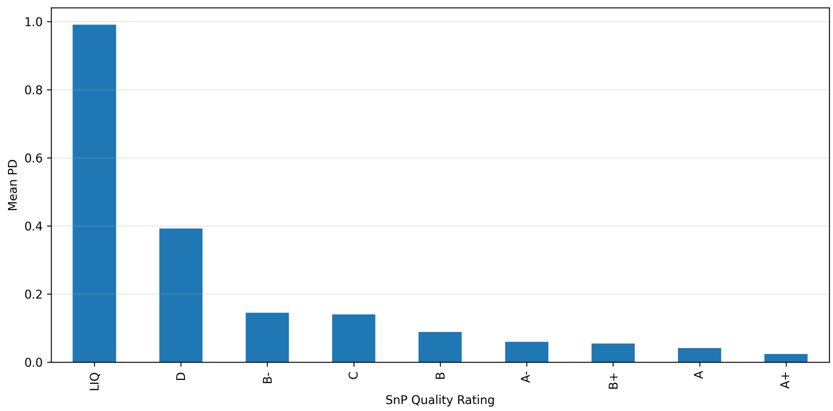


Figure 1: Mean probability of default by S&P Quality Rating

Notes: This figure plots the mean probability of default (PD) for each S&P credit quality rating. "LIQ" denotes defaulted observations, while "D" indicates near-default status, reflecting severely compromised financial health. Risk-neutral PDs should be considered a lower bound; however, the ranking across ratings is consistent with expectations (LIQ $>$ D $>$ …$>$ A+), supporting the validity of the measure.

firm health in this analysis (Hull et al. (2005)).

Data - Biodiversity News and Risk Exposure

In this section, I describe the biodiversity variables employed in the analysis. I rely on three complementary measures from Giglio et al. (2023).

First, I use their news-based biodiversity index, constructed from New York Times articles between January 2000 and December 2023. Articles are classified as positive or negative using sentiment analysis models such as BERT, and the index is computed as the daily difference between negative and positive articles. For example, a value of 5 indicates five more negative than positive biodiversity articles on that day. I transform this daily series into a quarterly measure by summing within each quarter. This index serves as my main proxy for time-varying biodiversity news shocks. Its main limitation is reliance on a single media source and potential classification errors inherent in NLP models.

Second, I incorporate industry-level biodiversity exposure scores. These are based on a survey of more than 600 market professionals and academics, who were asked to evaluate GICS4 industries on a five-point Likert scale according to their exposure to biodiversity-related physical and transitional risks. The average of these responses yields a risk score for each industry. These scores are relatively stable over time, since industries such as paper manufacturing inherently depend on biodiversity resources (e.g., logging), while others such as media or software firms do not. In my analysis, I use these exposure scores to classify firms into high- and low-risk groups. Firms above the median of the risk distribution are defined as high-risk, and those below are

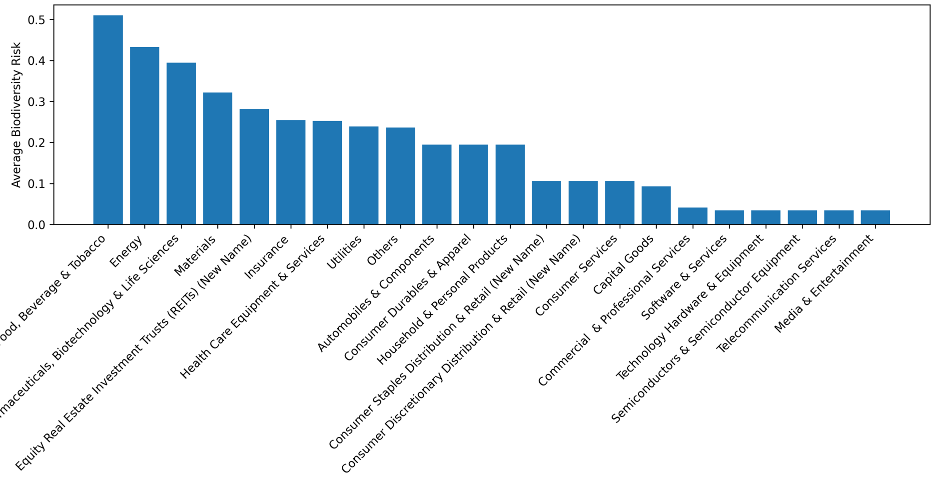


Figure 2: Biodiversity Risk by Industry

Notes: This figure plots the average biodiversity risk exposure by industry, based on data from Giglio et al. (2023).

defined as low-risk.

Finally, I use firm-level disclosure sentiment, also constructed by Giglio et al. (2023). This measure captures the difference between negative and positive biodiversity mentions in companies' 10-K filings. A higher value of the variable `"negative"` signals stronger firm-level risk exposure. Since this measure is annual, I assign the same value across all quarters of a given year. I primarily employ this disclosure-based measure as a control variable, since firms' own disclosures may influence how they react to biodiversity-related news shocks. Table A.5 gives a complete overview of the variables used and their definitions according to Giglio et al. (2023).

Figure 2 presents the average biodiversity risk across industries as reported by Giglio et al. (2023). The Food, Beverages, and Tobacco sector shows the highest exposure, reflecting its reliance on biodiversity-intensive commodities such as soy, timber, beef, and coffee. Energy, Utilities, and Materials also face elevated risk, given their direct interaction with natural resources (e.g., wind, water, and minerals). The Pharmaceutical and Healthcare sector ranks high as well, since many medicines depend on natural ingredients. By contrast, Communication, Media, and Software sectors are classified as low-risk, reflecting limited biodiversity dependence.

Summary Statistics - Levels or Changes?

Table 1 provides an overview of the sample composition across risk groups. The high-risk basket comprises 32,072 firm-quarter observations from 662 firms across 12 industries, while the low-risk basket contains 25,027 observations from 500 firms across 10 industries.

To examine potential structural differences between the two groups, I conduct a summary statis-

Variable/Metric	Low-Risk	High-Risk
Observations	25027	32072
Industries	10	12
Firms	500	662

Table 1: Summary statistics for low-risk and high-risk groups

Notes: This table summarizes the number of observations, industries, and firms in each risk basket. High-risk firms are those with an average biodiversity risk score above the median of the distribution, while low-risk firms fall below the median.

tics analysis for the full sample period (2006–2023) and perform t-tests to assess whether the levels of key firm fundamentals differ significantly across them.

Table C.2 compares the summary statistics of firm fundamentals across the two risk groups. The results indicate systematic differences in levels. High-risk firms exhibit a higher average implied market value of assets[8] (16,102.038 million USD) compared to low-risk firms (14,351.392 million USD), with a p-value below 0.05 confirming significance. They also carry significantly more debt on average (7,940.994 million USD versus 6,217.115 million USD), both in short- and long-term maturities, and incur significantly higher costs, including inventory, cost of goods sold, raw materials, and overall operating expenses. In terms of market variables, the natural log of equity volatility is lower for low-risk firms (–3.107) than for high-risk firms (–3.138), corresponding to an average volatility of 0.0447 versus 0.0434, respectively[9]. Low-risk firms also deliver significantly higher equity returns on average. Finally, average default risk is significantly greater among high-risk firms (0.059) compared to low-risk firms (0.054).

This finding indicates that firms in the two risk groups are systematically different in levels. Direct comparisons could therefore introduce bias, since differences in responses to biodiversity news may be confounded by pre-existing disparities. To address this concern, I examine the summary statistics of the first differences of these variables and conduct t-tests on their quarterly changes.

Table 2 presents a complementary perspective by focusing on quarter-to-quarter changes in firm fundamentals rather than their levels. These changes are highly dispersed, and no statistically significant differences emerge between the low- and high-risk groups. The large standard deviations within both groups indicate that, even where mean changes differ, the underlying dis-

[8]The Variables “Market Impied Asset Value”, “Implied Asset Volatility” and “Probability of Default” are obtained from employing the merton model in the data. The “Market Impied Asset Value” is different from the book value of assets reported in the balance sheets. It implies the risk-neutral market-value of the assets based on current market prices, rather than purchase price of the physical assets. The “Implied Asset Volatility” refers to the volatility of the asset value, rather than the volatility of the stocks. Detailed calculations of these variables are presented in Appendix Section B.

[9]The natural log of volatility is converted back into volatility units using the exponential transformation. For example, $e^{-3.107} \approx 0.0447$ for low-risk firms and $e^{-3.138} \approx 0.0434$ for high-risk firms.

Variable/Metric	Low-Risk Mean (1)	Low-Risk Std (2)	High-Risk Mean (3)	High-Risk Std (4)	t-stat (5)	p-value (6)
Observations	25027.000		32072.000			
Industries	10.000		12.000			
Firms	500.000		662.000			
Probability of Default^a	0.001	0.220	0.000	0.216	0.200	0.841
Log Volatility (Equity)	-0.000	0.384	-0.000	0.400	-0.014	0.989
Equity log returns	-0.000	0.315	-0.000	0.338	0.029	0.977
Short Term Debt	32.904	3498.183	43.289	2649.883	-0.386	0.699
Long Term Debt	55.140	1539.862	65.050	1419.864	-0.781	0.435
Interest Expense	0.432	31.139	0.629	45.275	-0.607	0.544
Implied Market Value of Assets^b	352.996	10884.453	239.334	6729.596	1.435	0.151
Implied Asset Volatility^c	-0.000	0.025	-0.000	0.029	0.159	0.874
Market Value of Equity	353.583	10821.272	238.776	6713.182	1.457	0.145
Total Debt	88.043	3446.883	108.340	2716.088	-0.757	0.449
Cost of Goods Sold	16.000	571.572	17.764	908.570	-0.280	0.779
Operating Expenses	22.438	776.307	21.905	947.374	0.073	0.942
Total Inventory Cost	13.700	3668.570	8.859	711.283	0.204	0.839
Inventory Cost of Raw Materials	0.983	813.564	2.494	558.320	-0.249	0.803
Net Profit	-3.269	420.002	-3.132	397.713	-0.039	0.969

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *All the coefficients and standard errors are rounded to the third decimal place. All values are winsorised using the full sample. Columns (1) and (3) represent the group means of quarterly changes of the variables. Columns (2) and (4) represent variation in these quarterly changes. The t-test and corresponding p-values are reported in columns (5) and (6) respectively.* a, b, c: *These variables are derived from the merton model. Market implied asset value is different from the book value of assets. Implied asset volatility is the volatility of assets, not equity. Probability of default is a proxy for the firm's health. See Appendix B(ii).*

Table 2: Summary statistics of changes by risk basket

tributions remain wide and overlapping. This is an important observation: while firms in high- and low-risk industries are fundamentally different in their characteristics—an outcome to be expected given sectoral heterogeneity—there is little evidence that their short-term dynamics systematically diverge.

This distinction matters for the empirical strategy. Direct level comparisons could introduce bias, as pre-existing disparities in fundamentals may confound the interpretation of group differences. By contrast, the focus on changes mitigates this concern, since the quarter-to-quarter dynamics appear comparable across groups. Put differently, although the two sets of firms operate at different baseline levels, the evolution of their fundamentals over time is subject to similar variability. This justifies basing the subsequent analysis on changes in these variables rather than their levels, thereby enabling a more meaningful assessment of how firms with differing biodiversity risk exposures co-move in response to news shocks.

Empirical Framework

The empirical strategy examines the impact of negative biodiversity news shocks on firms in the two risk baskets defined above. Specifically, I analyze how firm fundamentals respond to such shocks in the post-Aichi period (2021–2023) compared to the Aichi period (2006–2020). Although the Aichi Targets were formally adopted in 2010 with a 2011–2020 horizon, the Global

Biodiversity Outlook Committee concluded that none of the targets were achieved. I therefore define the Aichi period more broadly as 2006–2020 and contrast it with the stricter post-Aichi regime from 2021 onward.

To estimate these effects in a cross-sectional setting of the Aichi and postAichi periods, I run separate regressions for each firm fundamental and for credit risk in the two periods. The baseline specification is given by Equation (3).

$$\delta Y_{i,g,t,q} = \beta_0 + \beta_1 \cdot N_{t,q} + \beta_2 \cdot (R_g \cdot N_{t,q}) + \beta_3 \cdot N_{t,q-1} + \beta_4 \cdot D_t + \beta_5 \cdot \delta Y_{i,g,t,q-1} + \gamma_g + \gamma_t + \gamma_c + \epsilon_{i,g,t,q} \quad (3)$$

In Equation (3), $\delta Y_{i,g,t,q}$ denotes the change in variable Y for firm i in sector g, year t, and quarter q. $N_{t,q}$ is the biodiversity news shock in quarter q of year t, standardized in the full sample to ensure economic interpretability. The dummy variable R_g equals 1 if the firm belongs to a high-risk sector and 0 otherwise. The coefficient of the news shock is therefore β_1 for low-risk firms ($R_g = 0$) and $\beta_1 + \beta_2$ for high-risk firms ($R_g = 1$). The coefficient β_2 captures the divergence in responses between high-risk and low-risk firms to biodiversity news shocks.

I control for lagged news shocks from the previous quarter, $N_{t,q-1}$, to capture delayed responses in firm fundamentals. In addition, I include yearly disclosures of negative biodiversity sentiment in 10-K reports, denoted by D_t, to account for the possibility that such disclosures influence firm reactions. To address autocorrelation in the panel regressions, I also include the lagged dependent variable, $\delta Y_{i,g,t,q-1}$. I include year fixed effects (γ_t), industry fixed effects (γ_g), and credit-quality fixed effects (γ_c). Firm fixed effects are not included due to multicollinearity concerns[10]. The fixed effects absorb any year-specific, industry-specific, or credit-quality-specific influences. This is particularly important because the sample spans turbulent periods such as the COVID-19 pandemic, which systematically affected all firms. Moreover, industries have time-invariant characteristics, and firms differ systematically by credit rating. Controlling for these factors allows me to isolate the impact of negative biodiversity news shocks on firm fundamentals. Since the news shock is at a quarterly level and the risk classification is at the industry level, I report two-way clustered standard errors at the industry and quarter level. This accounts for correlation in residuals both across firms within the same industry over time and across industries within the same quarter[11].

[10] The sample comprises 1,162 firms, which would require 1,161 firm fixed effects. In this setting, the interaction of risk and news shocks is largely absorbed by the high-dimensional firm dummies, causing the design matrix to lose full rank and preventing estimation. To avoid this problem, I instead employ 21 industry fixed effects.

[11] Following Cameron et al. (2011), the two-way cluster-robust variance estimator is

$$\widehat{\text{Var}}(\hat{\beta}) = (X'X)^{-1}\left(\widehat{V}_{\text{industry}} + \widehat{V}_{\text{quarter}} - \widehat{V}_{\text{industry}\cap\text{quarter}}\right)(X'X)^{-1}.$$

In this empirical model, I treat biodiversity news shocks as exogenous. A key limitation, however, is that biodiversity news may partly capture firm-specific events (e.g., logging incidents that generate headlines). While the lag specification allows for gradual adjustment, it does not fully resolve potential endogeneity. Ideally, one would construct a leave-one-out news index that excludes articles linked to the focal firm, but this is not feasible with the available Giglio et al. (2023) data. A further limitation is that the industry-level exposure scores may reflect risks beyond biodiversity. For instance, high-risk industries such as energy and materials were also disproportionately affected by shocks around 2020, including the COVID-19 pandemic and U.S. trade policy. If such events systematically coincide with biodiversity exposure, the observed associations may partly reflect confounding factors. For these reasons, I interpret the estimates as associations rather than strictly causal effects.

But the question remains whether these divergences actually increased or decreased relative to the pre-Aichi period. Separate regressions cannot answer this directly, since the estimated coefficients are not comparable across disjoint samples. To address this, I pool the full sample and introduce a triple interaction term between biodiversity news shocks, risk exposure, and a post-Aichi indicator. Equation 4 allows me to test formally whether the divergence between high- and low-risk firms changed after the Aichi Targets expired, relative to the earlier period.

$$\begin{aligned} \delta Y_{i,g,t,q} = &\beta_0 + \beta_1 N_{t,q} + \beta_2 (R_g \cdot N_{t,q}) + \beta_3 (Post_t \cdot N_{t,q}) \\ &+ \beta_4 (Post_t \cdot R_g \cdot N_{t,q}) + \beta_5 N_{t,q-1} + \beta_6 D_t + \beta_7 \delta Y_{i,g,t,q-1} \\ &+ \gamma_g + \gamma_t + \gamma_c + \epsilon_{i,g,t,q} \end{aligned} \tag{4}$$

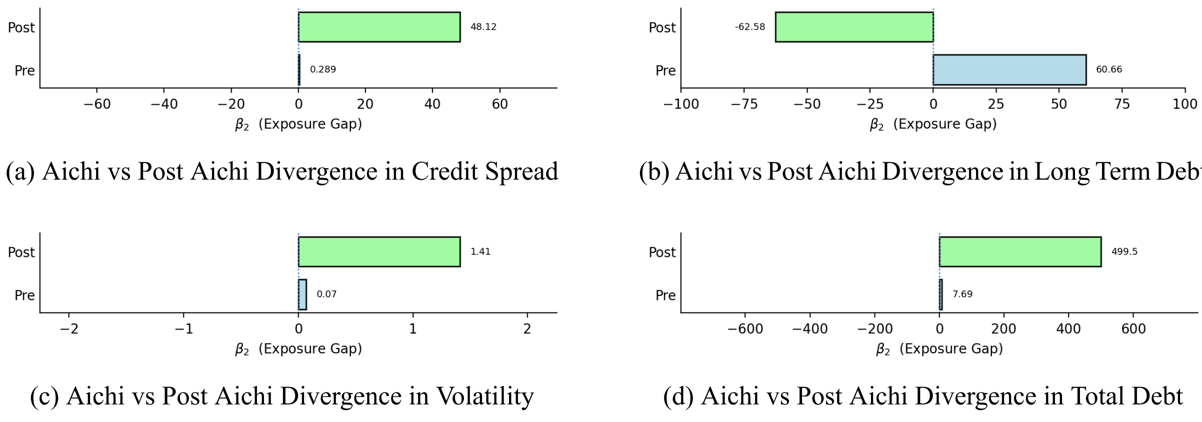
Equation 4 augments the baseline specification with an interaction term for the post-Aichi period. Here, $Post_t$ is a binary indicator equal to one for observations in the post-Aichi period (2021–2023) and zero otherwise. The coefficient β_1 measures the effect of negative biodiversity news shocks on low-risk firms during the Aichi period. The interaction term β_2 captures the divergence between high- and low-risk firms in the Aichi period, while β_3 represents the change in sensitivity of low-risk firms to news shocks in the post-Aichi period. The triple interaction term, β_4, is of primary interest: it measures how the divergence between high- and low-risk firms evolves in the post-Aichi period relative to the Aichi period. Equation 4 thus decomposes the effect of biodiversity shocks on credit spreads across firm risk groups and time periods. The

This relaxes the assumption of independence by allowing Cov$(\varepsilon_{i,t}, \varepsilon_{i,s}) \neq 0$ for all firms in the same industry across time, and Cov$(\varepsilon_{i,t}, \varepsilon_{j,t}) \neq 0$ for all firms in the same quarter across industries. Independence is only imposed across different industries in different quarters. Unlike industry–quarter cell clustering, this avoids assuming independence across time within industries or across industries within quarters.

coefficient β_1 captures the baseline response of low-risk firms in the Aichi period. Adding β_3 to this baseline ($\beta_1 + \beta_3$) gives the response of low-risk firms in the post-Aichi period. For high-risk firms in the Aichi period, the relevant coefficient is $\beta_1 + \beta_2$. Finally, for high-risk firms in the post-Aichi period, the full effect is $\beta_1 + \beta_2 + \beta_3 + \beta_4$. The remaining coefficients remain the same as equation 3. The coefficient β_4 thus identifies whether the divergence widened or narrowed after the expiration of the Aichi Targets: the null hypothesis is $H_0 : \beta_4 = 0$, i.e. no change in divergence across periods. A positive β_4 indicates that high-risk firms became more sensitive to biodiversity news relative to low-risk firms in the post-Aichi period, while a negative β_4 suggests the opposite. Standard errors are clustered two-way at the industry and quarter level to account for within-group correlation over time and across sectors.

Results and Discussion

The regression estimates from equations 3 and 4 provide associative evidence on how firm risk and financing conditions evolve with biodiversity news shocks in the Aichi and post-Aichi periods. Since the coefficients are obtained on changes in probability of default (δPD), I translate them into changes in credit spreads using Equation (1), which allows a more intuitive comparison across firms. This calculation assumes the standard assumptions of $LGD = 60\%$ for a one-year outlook on debt(maturity (T) = 1 year).



(a) Aichi vs Post Aichi Divergence in Credit Spread

(b) Aichi vs Post Aichi Divergence in Long Term Debt

(c) Aichi vs Post Aichi Divergence in Volatility

(d) Aichi vs Post Aichi Divergence in Total Debt

Figure 3: Credit spread changes across risk groups and periods

Notes: This figure reports the coefficients β_2 estimated from Equation 3, which measure the divergence in responses between high- and low-risk groups to a 1σ increase in negative biodiversity news shocks. Panel (a) shows the divergence in credit spreads, Panel (b) in long-term debt, Panel (c) in volatility, and Panel (d) in total debt. In all panels, the light blue bars correspond to the Aichi period (2006–2020), while the light green bars correspond to the post-Aichi period (2021–2023). For Panel (c), log volatility is transformed using $100(e^b - 1)$, where b is the estimated coefficient on log volatility.

I start with discussing the results from the baseline regression, highlighted in equation 3. Table D.1 reports the baseline estimates for the Aichi period. A one standard deviation increase in negative biodiversity news is associated with a significant rise in default risk, higher equity market volatility, and lower equity returns, all consistent with intuition. These effects are statistically significant for both low-risk firms (captured by β_1) and high-risk firms (captured by $\beta_1 + \beta_2$), confirming that biodiversity shocks deteriorate credit conditions across the board. However, the interaction term β_2, which measures the cross-sectional gap, is not significant in this period. In Table D.2, I document the coefficients for the baseline regression in the post-Aichi period. The results reveal a striking change. While both high- and low-risk firms face significant declines in PD and volatility following biodiversity shocks, the cross-sectional differences are now statistically significant, indicating that creditors increasingly discriminate between risk groups.

Figure 3 illustrates this difference in cross-sectional divergence in the Aichi and the post-Aichi periods. Panel 3a shows a significant widening of the credit spread gap by 48 basis points in the post-Aichi period, showing high-risk firms are penalized more heavily. A similar shift appears in equity markets: in the Aichi years, a one standard deviation increase in news shocks was associated with an incremental volatility of only 0.07%, whereas in the post-Aichi period this effect rose sharply to 1.41%(as shown in figure 3c)[12]. Debt dynamics also exhibit this pattern: panel 3b shows that the divergence in long-term debt issuance shrinks significantly in the post-Aichi period, while panel 3d documents a significant increase in the total debt gap. I return to this point in the subsequent analysis and explore why this divergence is particularly interesting and economically meaningful.

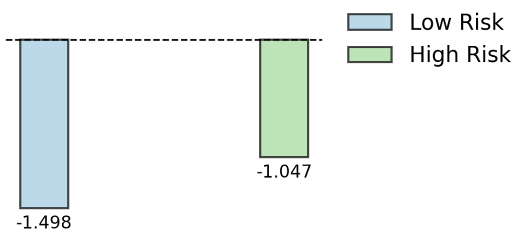
Taken together, the descriptive regressions show that during the Aichi period, firms reacted as if biodiversity shocks were largely unanticipated, with both risk groups moving in the same direction and without significant divergence. In the post-Aichi period, however, the gap between high- and low-risk firms widened substantially, even as overall credit and market conditions improved in response to negative news shocks. To trace this cross-period evolution more formally, I turn to the estimates from Equation 4, reported in Table D.3.

I begin the cross-period analysis with credit spreads, as they provide the most direct measure of how creditors reprice firm risk in response to biodiversity news shocks. Figure 4a shows that the sensitivity of credit spreads to a one standard deviation increase in negative biodiversity news shocks declined from the Aichi to the post-Aichi period for both high- and low-risk firms[13].

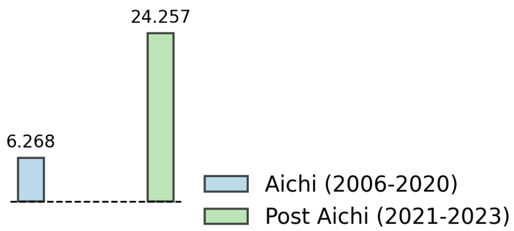
This overall reduction is notable, since the post-Aichi years coincide with a stricter regulatory

[12] Exponentiation is used in two distinct contexts. First, to recover levels from logged values (e.g., $e^{-3.107} \approx 0.0447$ gives the volatility level). Second, when interpreting regression coefficients on logged dependent variables, the percentage effect is calculated as $100(e^b - 1)$.

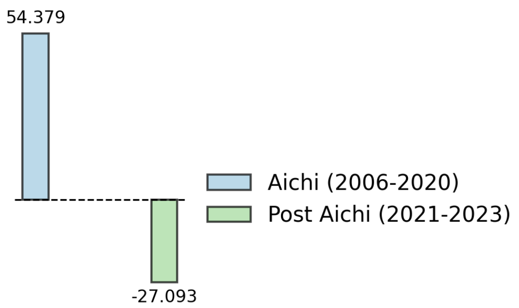
[13] Each bar in figure 4a represents $\frac{\delta CS_{i,post} - \delta CS_{i,pre}}{\delta CS_{i,pre}}$, where $i = \{High\ Risk\ ,\ Low\ Risk\}$.



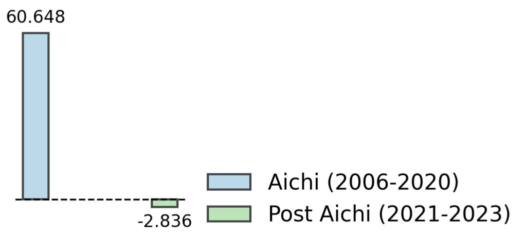
(a) % Change from Aichi - Post Aichi Period



(b) Relative Gap in Aichi and Post Aichi Period



(c) Low-Risk



(d) High-Risk

Figure 4: Credit spread changes across risk groups and periods

Notes: This figure reports coefficients from Equation 4 for the dependent variable δPD, transformed into credit spreads (δCS) using Equation 1. The coefficients represent the change in credit spreads (in bps) associated with a 1σ increase in negative biodiversity news shocks. Panel (a) shows the percentage change in δCS from the Aichi period (2006–2020) to the post-Aichi period (2021–2023). The light blue bar indicates high-risk firms; the light green bar indicates low-risk firms. Panel (b) plots the relative gap in spread changes ($\delta CS_{h,t} - \delta CS_{l,t}$) across the two periods, with the light blue bar for the Aichi period and the light green bar for the post-Aichi period. Panels (c) and (d) display the transformed coefficients of Equation 4 for δPD: in Panel (c), light blue = low-risk (Aichi), light green = low-risk (post-Aichi); in Panel (d), light blue = high-risk (Aichi), light green = high-risk (post-Aichi).

environment, which one might expect to amplify rather than dampen the pricing of biodiversity risk. The improvement is also uneven across firm types: low-risk firms experienced a stronger narrowing of spreads, while the reduction for high-risk firms was about 45 basis points smaller. In relative terms, this amounts to a roughly 30%[14] weaker improvement for high-risk firms compared to their low-risk peers[15]. Figure 4b highlights this divergence directly by plotting the relative penalty, defined as the difference in spread adjustments between the two groups $(\delta CS_{h,t} - \delta CS_{l,t})$[16]. In the Aichi period, the credit spread penalty was about 6 bps and in the post-Aichi period about 24 bps, though both are individually insignificant. However, the increase of roughly 18 bps between the two periods is statistically significant at the 10% level. While the widening penalty is intuitive, it raises a further question: why do credit spreads appear to decline—implying improved credit conditions—in association with negative biodiversity news shocks in the post-Aichi period? Figures 4c and 4d show that both groups exhibit lower post-Aichi coefficients, with low-risk firms experiencing a reduction in spreads of about 27 bps and high-risk firms a much smaller improvement of roughly 3 bps[17]. Table D.3 presents a similar pattern in equity markets. During the Aichi period, the stocks of low-risk firms showed an inignificant volatility increase of 1.98% linked to a one standard deviation rise in shocks, but this turned into a significant 3.91% decline in the post-Aichi years. High-risk firms also shifted from a significant volatility increase of 2.34% in the Aichi period to a significant decline of 2.55% post-Aichi. In other words, both credit and equity markets appear to treat biodiversity shocks more leniently after 2020. This result is particularly striking given the backdrop of stricter regulations and compliance pressures. To better understand this anomaly, I next examine the borrowing structures of firms.

Figure 5 highlights a striking pattern in the way short-term debt is associated with biodiversity news shocks. Panel 5a shows that low-risk firms took on very little short-term debt during the Aichi period (2006–2020), but in the post-Aichi period (2021–2023) they began actively deleveraging when shocks occurred. By contrast, Panel 5b shows that high-risk firms consistently relied on higher levels of short-term borrowing in association with shocks across both periods.[18].

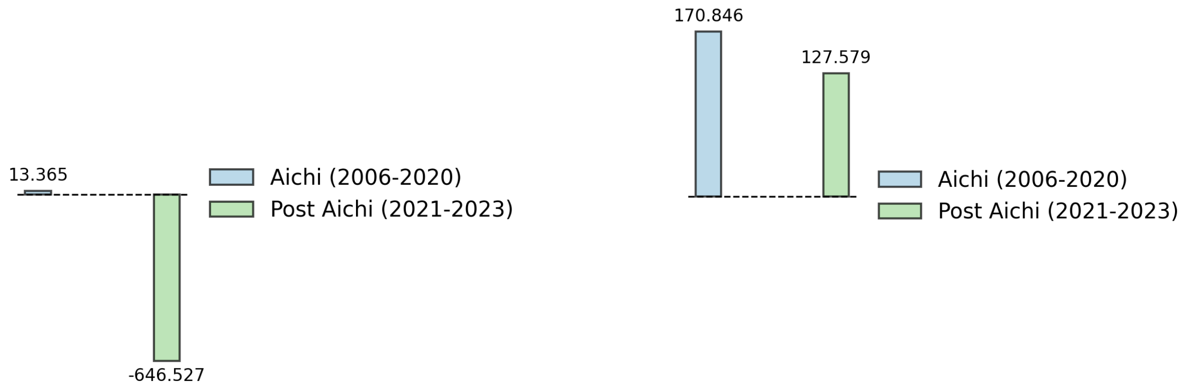
[14] $\frac{High-Low}{Low} = \frac{-1.047-(-1.498)}{-1.498}$

[15] This 30% rise in credit risk is denoted in table D.3, Interaction (β_4) coefficient for the variable PD,significant at 10% level.

[16] Each bar indicates $\delta CS_{h,t} - \delta CS_{l,t}$, for group $h = \{High\ Risk\}$ and $l = \{Low\ Risk\}$ in period $t = \{Pre\ Aichi\ ,\ Post\ Aichi\}$.

[17] The coefficients are estimated by the equation 4. For low-risk firms in the Aichi period, the coefficeints are β_1. In the Aichi period their coefficients become $\beta_1 + \beta_3$. For high-risk firms, their Aichi coefficients are $\beta_1 + \beta_2$, while the post-Aichi coefficient is $\beta_1 + \beta_2 + \beta_3 + \beta_4$.

[18] It is important to note that the calculations of the coefficients have been done using the coefficients of equation



(a) Low-Risk (b) High-Risk

Figure 5: Short Term Debt Acquisition Changes across Risk Brackets

Notes: This figure reports coefficients from Equation 4 for the dependent variable $\delta Short\_Term\_Debt$, interpreted as the change in short-term debt (in millions) associated with a 1σ increase in negative biodiversity news shocks. Panel (a) shows results for low-risk firms; Panel (b) for high-risk firms. In both panels, the blue bars represent the Aichi period (2006–2020) and the green bars the post-Aichi period (2021–2023).

Why do low-risk firms deleverage in association with biodiversity news shocks, while high-risk firms cannot? A sectoral perspective provides one possible explanation. Many high-risk firms in my sample operate in essential, resource-intensive industries such as food, energy, and pharmaceuticals. These sectors face heavy working-capital requirements, exposure to raw material costs, and ongoing compliance expenses, which make deleveraging during periods of heightened risk difficult. In fact, negative shocks may even increase their dependence on borrowing to secure supply chains or sustain production. By contrast, low-risk firms in sectors such as media and telecommunications typically have lighter capital needs and more flexible cost structures. This gives them scope to reduce leverage pre-emptively, thereby strengthening liquidity and signalling prudence to creditors. Firm size may reinforce this divergence: high-risk firms are significantly larger than low-risk firms, and their scale makes continuous external financing structurally indispensable. Moreover, figure 3b shows that the relative gap of long term debt acquisition between high- and low-risk firms narrowed. While, 3d highlights that post-Aichi, the relative gap in total debt acquisition widened in association with news shocks. Together with figure 5 and findings of table D.3, results indicate a pattern that the high-risk firms consistently leverage more than low-risk firms in association to news shocks in the post-Aichi period. This increased leverage is driven by an acquisition of more short term than long term debt (maturity

4. Using linear combinations of the coefficeints, in figure 5a, the light blue bar is the coefficient β_1, showing the coefficient of low-risk group in the Aichi period. The light green bar, showing the coefficient of low-risk group in the post-Aichi period is $\beta_1 + \beta_3$. In figure 5b, the light blue bar represents the coefficient of high-risk group in the Aichi period. It is represented by $\beta_1 + \beta_2$. Similarly, the light green bar represents the coefficient of high-risk group in the post-Aichi period ($\beta_1 + \beta_2 + \beta_3 + \beta_4$).

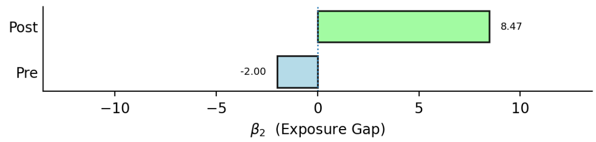


Figure 6: Aichi vs Post-Aichi Gap in Operating Expenses

Notes: This figure reports coefficients from Equation 3 for the dependent variable $\delta Operating\_Expenses$, interpreted as the difference in operating expense changes (in millions) between high- and low-risk firms associated with a 1σ rise in negative biodiversity news shocks. The light blue bar shows the relative gap during the Aichi period (2006–2020), and the light green bar the gap in the post-Aichi period (2021–2023).

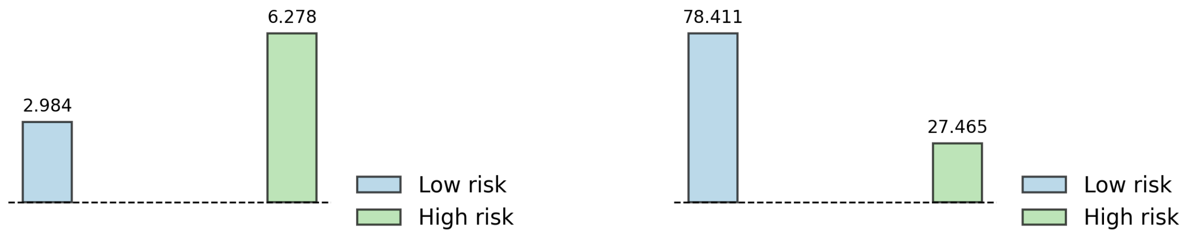
tightening). This finding is consistent with Ivanov et al. (2024)[19].

Figure 6 suggests that operating expenses rose more sharply for high-risk firms than for low-risk firms between the Aichi and post-Aichi periods. Although the difference is not statistically significant, the direction of the gap is consistent with the idea that resource-intensive firms may face heavier compliance and regulatory costs. These pressures could help explain why high-risk firms relied more heavily on borrowing, while low-risk firms, experiencing comparatively modest increases in operating costs, retained greater flexibility to adjust their financing structures in a more precautionary manner.

A similar yet significant divergence is visible in inventory stockpiling, shown in Figure 7. Low-risk firms expanded their raw material inventories from an insignificant \$2.9 million in the Aichi period to a significant \$78 million in the post-Aichi period, while high-risk firms increased inventories more modestly, from an insignificant \$6 million to an insignificant \$27 million. As a result, the relative gap between the two groups widened significantly in the negative direction, by about \$54 million. In the Aichi years, high-risk firms built larger inventories than low-risk firms (6m vs. 2m), but in the post-Aichi period the pattern reversed (27m vs. 78m). This reversal suggests that low-risk firms shifted toward a more precautionary stockpiling strategy, while high-risk firms adjusted only incrementally as operating costs and financing needs absorbed much of their capacity. Firm size may also play a role: larger, capital-intensive high-risk firms already carry substantial baseline inventories, making large marginal increases less feasible, whereas smaller low-risk firms can more readily pursue aggressive stockpiling in response to shocks.

High-risk firms show signs of greater caution in the post-Aichi period, a pattern consistent with a debt-disciplining mechanism. Because these firms could not reduce leverage, they relied more heavily on short-term borrowing to cover liquidity needs. The scrutiny and repayment pressure

[19]Authors find that carbon pricing policies (California's cap-and-trade and the federal Waxman-Markey bill) led high-emission firms to face shorter loan maturities, reduced access to long-term bank financing, higher borrowing costs, and greater reliance on shadow banks, with effects concentrated among private firms.



(a) Aichi Period (2006-2020)

(b) Post-Aichi Period (2021-2023)

Figure 7: Raw Material Inventory Acquisition Changes across Risk Brackets

Notes: This figure reports coefficients from Equation 4 for the dependent variable $\delta Inventory\_of\_raw\_materials$, interpreted as the change in raw material inventory (in millions) associated with a 1σ rise in negative biodiversity news shocks. Panel (a) shows results for the Aichi period (2006–2020) and Panel (b) for the post-Aichi period (2021–2023). In both panels, blue bars represent low-risk firms and green bars represent high-risk firms.

associated with short-term debt limited their room for risk-taking, pushing them into a more disciplined financial stance. Equity markets may have interpreted this discipline as a signal of reduced fragility, leading to milder volatility adjustments than in the Aichi years, while creditors responded with somewhat tighter but still improving spreads. Figure 4 illustrates this dynamic: credit conditions improved for both groups after 2020, but the gains were far larger for low-risk firms that could proactively deleverage and strengthen their balance sheets. For high-risk firms, by contrast, the improvement was modest, leaving the post-Aichi divergence between the two groups roughly 18 bps wider than in the Aichi baseline.

Conclusion

This paper provides early evidence that biodiversity-related news shocks influence firms' financing conditions beyond credit spreads, extending also to debt maturity structures in the post-Aichi period. The results indicate that creditors increasingly differentiate between high- and low-exposure firms. While both groups show fundamental improvements after the Aichi Targets expired, the adjustment is asymmetric: low-risk firms primarily undergo deleveraging, whereas high-risk firms face tighter liquidity conditions through a shift toward short-term borrowing, smaller reductions in credit risk and volatility, and evidence of constrained raw material stockpiling. Within the structural framework of Equation 1, these dynamics translate into a widening of credit spreads, consistent with creditors pricing biodiversity transition risks more severely into high-risk firms. In credit market terms, the post-Aichi widening is equivalent to high-risk firms being treated as if they had lost roughly one notch of credit quality. These findings align with recent evidence that biodiversity risks are increasingly financially material (Li and Naffa (2025); Giglio et al. (2023)), and they extend the literature by showing how such risks also affect corporate debt structures.

Several caveats are important when interpreting these results. First, biodiversity risk scores rely on evolving methodologies, and differences in measurement can influence results (Fliegel, 2024). Second, the Merton model implies that the reported divergence in default risk should be interpreted as a lower bound. Third, the analysis is based only on NASDAQ-listed firms and New York Times coverage, which may limit generalizability. Fourth, the short post-Aichi window constrains inference; ideally, the Kunming–Montréal Global Biodiversity Framework (2022) would provide a sharper testing ground, but data availability does not yet allow such an extension. Finally, high-risk biodiversity sectors overlap substantially with industries highly exposed to climate risks, meaning that part of the observed divergence may reflect broader climate- and trade-related developments rather than biodiversity shocks alone. For instance, the 2016 U.S. presidential election and its impact on climate policy expectations, or contemporaneous trade disputes and tariff negotiations, may have disproportionately affected high-risk industries. These events could influence debt maturities, refinancing costs, and inventory management, and if correlated with biodiversity risk classifications, they may bias the associations. Moreover, the results cannot fully disentangle supply constraints imposed by creditors from demand-side adjustments by firms, and both channels are likely at play.

Future work could extend the analysis by incorporating broader samples across regions and sectors, experimenting with alternative biodiversity risk indices, and developing refined identification strategies to isolate causal effects. Exploring the interplay between biodiversity regulation, capital market responses, and firm-level transition strategies could also shed light on the extent to which financial markets accelerate or hinder the global biodiversity agenda. Overall, the evidence presented here underscores that biodiversity transition risk is becoming an emerging and material determinant of corporate financing conditions in the post-Aichi regulatory era.

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Appendix

A. Data Description

i. Number of unique firms by GICS industry classification

Table A.1 provides an overview of the sample composition across Global Industry Classification Standard (GICS) sectors. The dataset comprises 1,162 unique, publicly traded non-financial firms listed on NASDAQ, distributed across 22 industries. Capital Goods, Pharmaceuticals & Biotechnology, and Health Care Equipment & Services represent the largest sectors in terms of firm counts, while smaller industries such as Consumer Staples Distribution & Retail and Household & Personal Products are represented by fewer than 15 firms each. This distribution underscores the heterogeneity of the sample, ensuring that the analysis captures a broad cross-section of industry-specific exposures to biodiversity risks.

Industry Name	Number of Firms
Capital Goods	151
Pharmaceuticals, Biotechnology & Life Sciences	128
Health Care Equipment & Services	96
Materials	86
Energy	77
Consumer Services	59
Commercial & Professional Services	58
Utilities	57
Insurance	56
Software & Services	49
Technology Hardware & Equipment	48
Consumer Durables & Apparel	46
Media & Entertainment	41
Other	38
Consumer Discretionary Distribution & Retail (New Name)	36
Semiconductors & Semiconductor Equipment	33
Food, Beverage & Tobacco	29
Automobiles & Components	25
Telecommunication Services	15
Equity Real Estate Investment Trusts (REITs) (New Name)	12
Household & Personal Products	12
Consumer Staples Distribution & Retail (New Name)	10

Table A.1: Number of unique firms by GICS industry classification

Notes: This table reports the number of unique firms by GICS industry classification. The sample includes 1,162 publicly traded non-financial firms listed on NASDAQ, distributed across 22 industries.

ii. Number of defaulting companies per year

Year	Number of Defaulted Firms
2006	1
2007	1
2008	3
2009	14
2010	11
2011	3
2012	3
2013	6
2014	3
2015	8
2016	4
2017	3
2018	3
2019	5
2020	8
2021	1
2022	2
2023	1

Table A.2: Number of defaulting companies per year

Notes: This table reports the annual number of defaulting firms in the sample. Bankruptcy data include both Chapter 7 and Chapter 11 filings, sourced from the Bankruptcy Research Database (2022) and matched to Compustat Capital IQ using `cusip9` identifiers.

Table A.2 reports the number of defaulting firms in the sample by year, with bankruptcy data sourced from the Bankruptcy Research Database (2022) and matched to Compustat Capital IQ via `cusip` identifiers. Notably, defaults are not evenly distributed over time but cluster around major economic disruptions. Following the onset of the Global Financial Crisis in 2008, defaults rose sharply, peaking in 2009 with 14 firms filing for bankruptcy and 11 firms in 2010. A second surge appears in 2020, coinciding with the COVID-19 shock, when eight firms defaulted in a single year.

iii. Identifying defaulting observations and joining datasets

Using the bankruptcy filing dates, I marked the corresponding defaulting quarter observations as "LIQ," which serves as my target indicator of default for testing the performance of the Merton model. From the Compustat Fundamentals Quarterly dataset, I collected firm-level information for each quarter, with the variables summarized in Table A.3.

The S&P quality rating provided in `"spcsrc"` assigns a quarterly credit quality score to each firm, as summarized in Table A.4. In principle, firms rated A+ should exhibit the lowest proba-

Variable	Description
cusip	Firm Level Identifier
fyearq	Year Identifier
fqtr	Quarter Identifier
mktvalq	Market Value of the Asset
xoprq	Total Operating Expenses
xintq	Total Interest Expenses
xsgaq	Total Selling, General and Administrative Expenses
atq	Assets (Total)
dlcq	Debt in Current Liabilities
dlttq	Debt in Long Term Liabilities
glaq	Gain or Loss after Tax
invrmq	Inventory of Raw Materials
invtq	Total Inventory
lctq	Total Current Liabilities
optrfrq	Risk Free Rate
cshoq	Shares Outstanding
spcsrc	SnP Quality Rating
gind	Gics Sector
cogsq	Cost of Goods Sold
dd1q	Long term debt due in one year

Table A.3: Variable List and Descriptions

Notes: This table describes the definitions of the various variables from the Compustat Capital-IQ, Fundamentals Quarterly dataset.

bility of default, while those rated D are expected to face the highest risk. To distinguish actual bankruptcies from low ratings, I marked defaulting quarters as "LIQ," indicating liquidation. This separates true default events from a D rating, which reflects severe financial distress but not necessarily bankruptcy.

Variable	Description
A+	Strong capacity to meet financial commitments, upper end of "A" category
A	Strong capacity to meet financial commitments
A-	Strong capacity, but somewhat more susceptible to economic changes
B+	More vulnerable to adverse conditions, but currently able to meet commitments
B	More vulnerable than B+, but currently meeting commitments
B-	Even more vulnerable than B; risk of default is more significant
C	Very high risk of default
D	Very poor financial discipline, near bankruptcy state
LIQ	Filed for bankruptcy (manually encrypted based on bankruptcy data)

Table A.4: Company Health Identifier

Notes: This table describes the credit quality categories used as firm health identifiers in the sample. Ratings from A+ to C follow the standard S&P long-term issuer credit ratings, where higher ratings indicate stronger capacity to meet financial commitments. Category D refers to firms in near-default condition, while LIQ represents firms that have formally filed for bankruptcy, manually matched to bankruptcy records. Together, these categories provide a consistent framework for distinguishing firm health and aligning probabilities of default with observable credit quality.

iv. Biodiversity Variables

Column	Description
negative	10K-Biodiversity-Negative Score: the number of negative biodiversity sentences minus the number of positive biodiversity sentences
transition_risk	Transition biodiversity risk exposure: share of the survey respondents who select each industry as being particularly affected by transition risk.
physical_risk	Physical biodiversity risk exposure: share of the survey respondents who select each industry as being particularly affected by physical risk.
average_risk	Survey-based Biodiversity Score: the simple average of transition and physical biodiversity risk exposure
net_neg_minus_positive_news	NYT Biodiversity News Index: the number of negative biodiversity articles minus the number of positive biodiversity articles on a given day

Table A.5: Biodiversity related columns description

Notes: This table provides detailed definitions of the biodiversity-related variables used in the analysis. All variables are sourced from Giglio et al. (2023). The measures combine survey-based industry exposures (transition and physical risk), firm-level disclosures (10-K sentiment scores), and media coverage (NYT biodiversity news index). The `net_neg_minus_positive_news` is my main variable fo interest. I control the regressions with the variable `negative`. I use the `average_risk` to bin the firms into low- and high-risk firms.

B. Estimating Default Probabilities with the Merton Model

i. The Merton Model

For the purpose of estimating the risk-neutral default probabilities, I use the option-valuation framework suggested by Merton (1974) building on Black and Scholes (1973). For empirically estimating the default probabilities, I replicate the methodology used by Afik et al. (2016).

The Merton model evaluates a firm's asset value and default risk using the market value of equity, the face value of debt, and the volatility of equity returns. It assumes that the firm has issued a single zero-coupon bond maturing at time T. Default occurs at maturity if the value of the firm's assets (A_T) is less than the face value of its debt (D). If the asset value exceeds the debt obligation, the firm repays its debt, and shareholders receive the residual value.

$$E_T = \max(A_T - D, 0) \tag{5}$$

This formulation allows the firm's equity to be interpreted as a European call option on the firm's assets, where the face value of debt acts as the strike price and the asset value as the underlying. Shareholders, like call option holders, receive a payoff only if the option expires in-the-money; otherwise, it expires worthless.

The model further assumes that the value of the firm's assets follows a Geometric Brownian Motion (GBM), given by:

$$dA = \mu_A \cdot A \cdot dt + \sigma_A \cdot A \cdot dW \tag{6}$$

where μ_A is the expected (continuously compounded) return on assets, σ_A is the asset return volatility, and dW is a standard Wiener process.
Applying the Black-Scholes option pricing framework, the value of equity as a call option on the firm's assets can be expressed as:

$$E = N(d)A - De^{-rT}N(d - \sigma_A\sqrt{T}) \tag{7}$$

$$d = \frac{\ln(A/D) + [r + 0.5\sigma_A^2]T}{\sigma_A\sqrt{T}} \tag{8}$$

Here, E is the market value of equity, r is the risk-free interest rate, and $N(\cdot)$ denotes the cumulative standard normal distribution function. A key limitation of this framework is that neither the value of the firm's assets (A) nor the asset volatility (σ_A) is directly observable. Therefore, an additional equation is needed to jointly estimate these values.
Jones et al. (1984) showed that, under the model assumptions, the relationship between equity volatility (σ_E) and asset volatility (σ_A) is given by:

$$\sigma_E = \frac{A}{E} \cdot \frac{\partial E}{\partial A} \cdot \sigma_A$$

Using the Black-Scholes formula, it can be shown that:

$$\frac{\partial E}{\partial A} = N(d)$$

Substituting this into the previous expression yields:

$$\sigma_E = \frac{A}{E}N(d)\sigma_A \tag{9}$$

Solving equations 7 and 9 simultaneously allows to recover the unobserved values of A and σ_A. These parameters can then be used to compute the firm's distance to default (DD), defined as:

$$DD = \frac{\ln\left(\frac{A}{D}\right) + [\mu_A - 0.5\sigma_A^2]T}{\sigma_A\sqrt{T}} \tag{10}$$

DD may be regarded as the normalized distance between the firm's asset value and the face value of its debt. As the log asset value is normally distributed under the GBM assumption, the probability of default (PD)—that is, the probability that the call option is not exercised—is given by:

$$PD = N(-DD) \tag{11}$$

Following the empirical specifications of Afik et al. (2016), I calibrate the model under alternative assumptions regarding the expected return on assets. This return is treated as deterministic, with three possible specifications: (i) equity return as a proxy for asset return, which tends to exaggerate volatility and responsiveness to small fluctuations; (ii) the risk-free rate, which yields risk-neutral probabilities of default; and (iii) the maximum of the risk-free rate and equity return, max(r_f, r_E). The second key hyperparameter concerns the debt threshold. Prior work (Bharath and Shumway (2008)) shows that long-term debt carries predictive power for default probabilities. For tractability, both Bharath and Shumway (2008) and the KMV model approximate the threshold as short-term debt plus one-half of long-term debt. In line with Afik et al. (2016), I conduct a grid search (Table B.1) to identify the calibration that delivers the best model performance.

ii. Model Performance Evaluation

For each model specification, I evaluate performance along two dimensions:

1. Discriminatory power (using AUC and pAUC), and
2. Model calibration (using the Brier Score).

The Area Under the Receiver Operating Characteristic Curve (AUC) is a threshold-independent measure of a binary classifier's discriminatory ability. Following Afik et al. (2016), I compute the AUC for each model specification to assess how effectively it distinguishes between defaulting and non-defaulting firms. Conceptually, the AUC represents the probability that a randomly chosen defaulting observation receives a higher predicted probability of default (PD) than a randomly chosen non-defaulting observation:

$$\text{AUC} = P(s_{\text{default}} > s_{\text{non-default}}).$$

Formally, it can be expressed as:

$$\text{AUC} = \frac{1}{N_1 N_0} \sum_{i \in \text{defaults}} \sum_{j \in \text{non-defaults}} \mathbf{I}(s_i > s_j),$$

where s_i and s_j denote the predicted scores for defaulting and non-defaulting observations, respectively, and N_1 and N_0 are the number of observations in each class.

Since the AUC is based on rank ordering rather than classification accuracy at a fixed cutoff, it provides a robust measure of discriminatory power. Importantly, it does not rely on a predefined default threshold.

In this context, the ROC curve plots the true positive rate (TPR) against the false positive rate (FPR) across all possible thresholds. A common refinement of AUC is the partial AUC (pAUC), which restricts attention to a specific region of the ROC curve—typically at low FPRs that are most relevant in credit risk applications. Formally, the pAUC between two bounds α and β is defined as:

$$\text{pAUC}(\alpha, \beta) = \int_{\alpha}^{\beta} \text{TPR}(t)\, dt,$$

where TPR(t) denotes the true positive rate at false positive rate t, and $0 \leq \alpha < \beta \leq 1$.

This measure emphasizes a model's discriminatory ability in operationally critical ranges. For example, restricting the FPR to 10% corresponds to evaluating how much TPR the model achieves while keeping misclassification of non-defaulting firms at or below this level. Such a focus is particularly important in credit risk, since false positives—erroneously classifying healthy firms as defaulting—can distort lending decisions and portfolio allocation.

An AUC of 1 corresponds to perfect discrimination, while an AUC of 0.5 reflects random predictions. Analogously, higher values of pAUC indicate stronger discriminatory performance within the chosen FPR bounds.

The Brier Score is a proper scoring rule that evaluates the accuracy of probabilistic predictions. For binary outcomes, it is defined as:

$$\text{Brier Score} = \frac{1}{N} \sum_{i=1}^{N} (s_i - y_i)^2,$$

where $s_i \in [0, 1]$ denotes the predicted probability of default for observation i, and $y_i \in \{0, 1\}$ is the realized outcome. Conceptually, it measures the mean squared error between predicted probabilities and actual outcomes.

The Brier Score jointly reflects two desirable features of probabilistic forecasts: *calibration* (how well predicted probabilities align with observed frequencies) and *sharpness* (the degree of confidence in predictions). A lower Brier Score indicates better calibration and overall predictive accuracy.

In default prediction, where class imbalance is common and default rates are often below 5%, Brier Scores tend to be small by construction. As highlighted by Khandani et al. (2010), even well-performing models may yield values well below 0.05. As a rule of thumb:

- Brier Score < 0.01: highly accurate and well-calibrated predictions,
- 0.01–0.05: moderate calibration,
- > 0.05: weak calibration or overconfident forecasts,
- ≈ 0.25: uninformative model, equivalent to predicting the unconditional base rate.

Thus, even seemingly small differences in Brier Scores can represent meaningful improvements in model calibration. Table B.1 reports the calibration and discrimination scores from the hyperparameter grid search.

k	r_f			Equity Return			$\mu_a^{\max}$		
	AUC	pAUC(0.1)	Brier	AUC	pAUC(0.1)	Brier	AUC	pAUC(0.1)	Brier
0.0	0.9589	0.4315	0.0406	0.9217	0.5615	0.0708	0.9328	0.4035	0.0406
0.1	0.9623	0.4280	0.0413	0.9206	0.5563	0.0741	0.9308	0.4013	0.0416
0.2	0.9567	0.4305	0.0418	0.9295	0.5607	0.0770	0.9396	0.3896	0.0421
0.3	0.9560	0.4235	0.0423	0.9278	0.5448	0.0796	0.9384	0.3973	0.0426
0.4	0.9554	0.4230	0.0427	0.9261	0.5528	0.0821	0.9372	0.3790	0.0430
0.5	0.9548	0.4221	0.0430	0.9243	0.5532	0.0843	0.9361	0.3909	0.0433
0.6	0.9542	0.4203	0.0433	0.9214	0.5452	0.0864	0.9351	0.3919	0.0436
0.7	0.9537	0.4209	0.0436	0.9200	0.5394	0.0883	0.9342	0.3933	0.0439
0.8	0.9532	0.4181	0.0438	0.9287	0.5446	0.0902	0.9333	0.3830	0.0442
0.9	0.9527	0.4168	0.0441	0.9276	0.5229	0.0920	0.9325	0.3809	0.0444
1.0	0.9523	0.4142	0.0443	0.9265	0.5300	0.0937	0.9317	0.3886	0.0446

Table B.1: Model performance under alternative calibration setups for the two-system Merton model.

Notes: This table reports the calibration results from a grid-search analysis of the two-system Merton model. The performance is evaluated under alternative specifications for μ_a (set equal to r_f, equity return, or $\mu_a^{\max}$) and across values of the scaling parameter k. Discriminatory power is assessed using AUC and partial AUC at 0.1 (pAUC(0.1)), while calibration fit is assessed using the Brier score. A higher AUC and pAUC indicate better discrimination, while a lower Brier score indicates better calibration. Based on these criteria, the specification with $k = 0.1$ and $\mu_a = r_f$ is selected as the preferred model.

Based on the grid search results reported in Table B.1, the calibration with $k = 0.1$ and $\mu_a = r_f$ delivers the highest discriminatory power (AUC = 96.23%) while maintaining a moderate Brier Score(0.0413). Since this outcome is consistent with the findings of Afik et al. (2016), I adopt the same calibration in my analysis.

Using this specification, I obtain three variables of interest: the *Market-Implied Asset Value*, the *Implied Asset Volatility*, and the *Probability of Default (PD)*. The Market-Implied Asset Value differs from the book value of assets reported in balance sheets, which are backward-looking and based on historical costs. Instead, it reflects the firm's enterprise value as implied by market information. Correspondingly, the Implied Asset Volatility measures the volatility of this enterprise value, providing a forward-looking assessment of asset risk. The PD represents the risk-neutral probability of default implied by this structural setup.

C. Apples to Oranges? Summary Stats

i. Summary Stats - Full Sample

Variable	Mean(1)	Std. Dev.(2)	Min(3)	Max(4)
Probability of Default^a	0.057	0.225	0.000	1.000
Log Volatility	-3.127	0.520	-4.193	-1.600
Equity Log Returns	0.016	0.205	-0.677	0.589
Short Term Debt	2786.933	6719.263	5.411	45318.160
Long Term Debt	3392.332	7409.359	0.000	47383.660
Interest Expense	41.561	83.144	-12.966	520.000
Market Implied Asset Value^b	13419.044	31052.247	166.536	204966.301
Implied Asset Volatility^c	0.048	0.028	0.014	0.715
Market Value (Equity)	12823.906	29793.260	152.328	196013.035
Total Debt	6205.999	13526.535	8.925	86417.860
Cost of Goods Sold	1368.919	3254.274	0.752	23093.000
Operating Expense	1682.431	3898.490	7.328	27432.240
Total Inventory Cost	686.423	1566.761	0.000	10243.000
Inventory Cost of Raw Materials	183.375	467.049	-285.959	3303.302
Net Profit	4.497	201.781	-561.793	674.111

Notes: Figures are rounded to the 3rd decimal place. To mitigate the influence of extreme values, all variables are winsorised at the 1st and 99th percentiles here and in subsequent analysis.
a, b, c: These variables are derived from the merton model. Market implied asset value is different from the book value of assets. Implied asset volatility is the volatility of assets, not equity. Probability of default is a proxy for the firm's health. See Appendix B(ii).

Table C.1: Descriptive statistics (mean, standard deviation, minimum, maximum)

ii. Summary Stats by Levels

Variable/Metric	Low Risk Mean (1)	Low Risk Std (2)	High Risk Mean (3)	High Risk Std (4)	t-stat (5)	p-value (6)
Observations	25027.000		32072.000			
Industries	10.000		12.000			
Firms	500.000		662.000			
Probability of Default^a	0.054	0.220	0.059	0.229	-2.603	0.009
Log Volatility (Equity)	-3.107	0.485	-3.138	0.579	7.062	0.000
Equity log returns	0.018	0.224	0.014	0.238	2.171	0.030
Short Term Debt	2818.540	13973.749	3589.755	10040.295	-7.372	0.000
Long Term Debt	3398.575	16539.034	4351.239	9791.662	-8.075	0.000
Interest Expense	41.652	207.598	53.466	125.672	-7.939	0.000
Implied Market Value of Assets^b	14351.392	68180.530	16102.038	41590.953	-3.576	0.000
Implied Asset Volatility^c	0.048	0.033	0.049	0.040	-3.662	0.000
Market Value of Equity	13818.379	66725.522	15417.601	40511.427	-3.341	0.001
Total Debt	6217.115	29617.621	7940.994	18933.659	-8.018	0.000
Cost of Goods Sold	1118.786	3104.173	1841.863	5607.067	-19.569	0.000
Operating Expenses	1490.210	4587.948	2131.986	6098.836	-14.348	0.000
Total Inventory Cost	567.467	5084.823	817.832	2072.261	-7.329	0.000
Inventory Cost of Raw Materials	165.133	834.457	238.177	747.080	-10.862	0.000
Net Proft	2.770	343.129	11.590	306.123	-3.194	0.001

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *All the coefficeints and standard errors are rounded to the third decimal place. All values are winsorised using the full sample. The columns (1) and (3) represent the group means of quarterly changes of the Variables. Columns (2) and (4) represent variation in these quarterly changes. The t-test and corresponding p-values are reported in columns (5) and (6) respectively.* a, b, c: *These variables are derived from the merton model. Market implied asset value is different from the book value of assets. Implied asset volatility is the volatility of assets, not equity. Probability of default is a proxy for the firm's health. See Appendix B(ii).*

Table C.2: Summary statistics of levels by risk basket

D. Regression Result Tables

i. Aichi Period (2006-2020)

Variable	Intercept	β_1	β_2	$\beta_1 + \beta_2$	# Obs	R^2	DW-Stat	FE	Lagged Y	Lagged News
PD	-0.0539^{***} (0.011)	0.0008^{***} (0.000)	4.81E−05 (0.000)	0.0008^{***} (0.0002)	46765	0.218	2.25	Yes	Yes	Yes
Log Volatility	-0.2549^{***} (0.000)	0.0034^{***} (0.000)	0.0007 (0.000)	0.0028^{***} (0.000)	46765	0.195	2.19	Yes	Yes	Yes
Log Equity Returns	0.0898^{***} (0.011)	-0.0033^{***} (0.000)	-0.0002 (0.000)	-0.0035^{***} (0.0002)	46765	0.292	2.34	Yes	Yes	Yes
Short Term Debt	271.3373^{*} (152.605)	36.5098 (49.212)	-17.8283 (37.894)	18.6815 (30.037)	46765	0.235	2.23	Yes	Yes	Yes
Long Term Debt	111.5516 (102.448)	-132.0766^{***} (44.579)	60.6586^{**} (27.647)	-71.4188^{***} (25.901)	46765	0.107	2.031	Yes	Yes	Yes
Interest Expense	9.9938^{**} (3.352)	2.4401^{***} (1.015)	-1.3654 (0.858)	1.0747^{*} (0.5722)	46765	0.002	2.002	Yes	Yes	Yes
Market Value of Equity	948.3339^{***} (208.104)	-206.2914^{***} (46.716)	-38.604 (61.521)	-244.8954^{***} (52.5050)	46765	0.013	2.008	Yes	Yes	Yes
Total Debt	484.433^{*} (224.813)	14.484 (49.268)	7.6897 (46.462)	22.1739 (35.2515)	46765	0.077	2.131	Yes	Yes	Yes
Market Implied Asset Value	1037.9447^{***} (244.846)	-134.1051^{***} (44.569)	-56.84 (61.521)	-190.9451^{***} (55.2900)	46765	0.012	2.001	Yes	Yes	Yes
Implied Asset Volatility	$-1.728e-09^{***}$ (0.000)	0.0013 (0.014)	-0.0003 (0.001)	0.0010 (0.021)	46765	0.192	2.192	Yes	Yes	Yes
Cost of Goods Sold	48.1334^{***} (23.508)	21.3964^{***} (6.983)	-4.3186 (6.884)	17.0818^{***} (6.4598)	46765	0.036	2.052	Yes	Yes	Yes
Operating Costs	77.1273^{***} (32.113)	23.1173^{**} (8.155)	-2.0008 (8.115)	20.3132^{***} (6.8661)	46765	0.051	2.057	Yes	Yes	Yes
Inventory Cost	112.9865 (73.117)	50.659 (27.539)	-47.43^{*} (15.677)	3.229 (15.677)	46765	0.007	2.074	Yes	Yes	Yes
Inventory Cost of Raw Materials	33.1603^{**} (16.581)	0.2604 (8.616)	0.6021 (6.030)	0.8625 (4.7839)	46765	0.171	2.35	Yes	Yes	Yes
Net Profit	13.3196 (9.122)	3.2831 (5.007)	-7.0450^{**} (3.545)	-3.7619 (3.0978)	46765	0.296	2.30	Yes	Yes	Yes

*Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All the coefficeints and standard errors are rounded to the third decimal place. All values are winsorised using the full sample. All the standard errors are clustered using two way cluster at the industry-quarter level. Standard errors are presented in parenthesis. β_1 represents the coefficient of news shock when $R_g = 0$. The coefficient of news shock when $R_g = 1$ is $\beta_1 + \beta_2$. The standard error and significance of the $\beta_1 + \beta_2$ coefficient is obtained by running a Wald t-test, where $SE(\beta_1 + \beta_2) = \sqrt{Var(\beta_1) + Var(\beta_2) + 2 \cdot Cov(\beta_1, \beta_2)}$. The variable $N_{t,q}$ is standardized. The Y variable is in real units. So the coefficients are interpretable as x natural unit change with respect to 1 standard-deviation rise in negative biodiversity news.*

Table D.1: Regression results – Aichi Period (pre 2021)

Looking across the Aichi-period regressions in Table D.1, the coefficients on β_2 which capture the differential effect of biodiversity news shocks for high-risk firms — are generally small and statistically weak, pointing to limited cross-sectional heterogeneity before 2021. Most estimates are close to zero and not significant, including for credit risk (PD), log volatility, debt structure, and inventory-related measures, suggesting that creditors and firms did not strongly differentiate between high- and low-risk exposures during this period.

ii. Post-Aichi Period (2020-2023)

Variable	Intercept	β_1	β_2	$\beta_1 + \beta_2$	# Obs	R^2	DW-Stat	FE	Lagged Y	Lagged News
PD	-0.001 (0.003)	-0.015^{***} (0.004)	0.008^{**} (0.003)	-0.007^{**} (0.003)	12804	0.141	2.22	Yes	Yes	Yes
Log Volatility (Equity)	-0.066^{***} (0.005)	-0.057^{***} (0.005)	0.014^{***} (0.004)	-0.043^{***} (0.005)	12804	0.178	2.075	Yes	Yes	Yes
Log Equity Returns	-0.075^{***} (0.004)	0.053^{***} (0.005)	-0.003 (0.004)	0.051^{***} (0.005)	12804	0.250	2.32	Yes	Yes	Yes
Short Term Debt	340.083^{**} (156.764)	-349.441^{*} (174.038)	520.653^{***} (193.011)	171.212^{*} (97.046)	12804	0.183	2.26	Yes	Yes	Yes
Long Term Debt	167.113 (131.987)	40.681 (33.862)	-62.583^{**} (26.523)	-21.902 (28.237)	12804	0.016	1.954	Yes	Yes	Yes
Interest Expense	-3.522^{**} (1.541)	4.810^{***} (1.328)	-1.362 (1.040)	3.448^{**} (1.346)	12804	0.186	1.79	Yes	Yes	Yes
Market Value of Equity	1596.737^{***} (403.515)	136.977 (206.250)	533.544^{*} (318.831)	670.520^{***} (219.418)	12804	0.012	2.051	Yes	Yes	Yes
Total Debt	554.198^{*} (329.067)	-343.381^{*} (180.519)	499.542^{*} (197.645)	156.161^{*} (88.341)	12804	0.151	2.22	Yes	Yes	Yes
Market Implied Asset Value	1555.506^{***} (369.845)	-177.674 (206.935)	807.179^{**} (344.773)	629.505^{***} (230.420)	12804	0.015	2.056	Yes	Yes	Yes
Implied Asset Volatility	-0.0032^{***} (0.000)	-0.0033^{***} (0.000)	0.0003^{***} (0.000)	-0.0029^{***} (0.0004)	12804	0.155	2.103	Yes	Yes	Yes
Cost of Goods Sold	109.807^{***} (38.235)	-14.804 (11.257)	10.887 (8.659)	-3.917 (14.660)	12804	0.063	1.81	Yes	Yes	Yes
Inventory Cost	48.686^{*} (25.186)	13.472 (19.158)	11.204 (14.464)	24.675 (16.265)	12804	0.025	1.984	Yes	Yes	Yes
Inventory Cost of Raw Materials	-2.508 (6.545)	86.219^{***} (31.370)	-100.437^{**} (43.714)	-14.218 (20.944)	12804	0.161	2.41	Yes	Yes	Yes
Operating Costs	133.977^{***} (46.621)	-6.425 (12.409)	8.472 (9.512)	2.047 (16.374)	12804	0.094	1.97	Yes	Yes	Yes
Net Profit	-1.908 (3.790)	44.119^{***} (9.687)	-0.836 (8.554)	43.282^{***} (6.798)	12804	0.202	2.28	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *All the coeffniceints and standard errors are rounded to the third decimal place. All values are winsorised using the full sample. All the standard errors are clustered using two way cluster at the industry-quarter level. Standard errors are presented in parenthesis. β_1 represents the coefficient of news shock when $R_g = 0$. The coefficient of news shock when $R_g = 1$ is $\beta_1 + \beta_2$. The standard error and significance of the $\beta_1 + \beta_2$ coefficient is obtained by running a Wald t-test, where $SE(\beta_1 + \beta_2) = \sqrt{Var(\beta_1) + Var(\beta_2) + 2 \cdot Cov(\beta_1, \beta_2)}$. The variable $N_{t,q}$ is standardized. The Y variable is in real units. So the coefficients are interpretable as x natural unit change with respect to 1 standard-deviation rise in negative biodiversity news.*

Table D.2: Regression results – Post Aichi period (2021–2023)

In the post-Aichi period (2021–2023), the β_2 coefficients reveal a clear shift toward significant cross-sectional divergence in firm responses to biodiversity news shocks. High-risk firms exhibit persistently higher sensitivity in key financing variables: their short-term debt reliance rises significantly, long-term debt falls, and market-implied asset values and volatilities adjust more negatively than for low-risk firms. At the operational level, inventory costs show a strong and significant decline for high-risk firms relative to low-risk firms, consistent with tighter liquidity discipline, while low-risk firms increase inventory accumulation and maintain stronger balance-sheet positions.

iii. Pooled Regression

Variable	Low risk pre-Aichi (1)	Low risk post-Aichi (2)	High risk pre-Aichi (3)	High risk post-Aichi (4)	Interaction term (5)
Probability of Default	0.009**	-0.005	0.010***	-0.000	0.003**
	(0.004)	(0.005)	(0.003)	(0.005)	(0.002)
Log Volatility (Equity)	0.020	-0.040***	0.023**	-0.026**	0.010*
	(0.013)	(0.012)	(0.012)	(0.012)	(0.006)
Log Equity Returns	-0.030***	-0.021**	-0.033***	-0.016	0.009
	(0.008)	(0.010)	(0.008)	(0.012)	(0.017)
Short Term Debt	13.365	-646.527***	170.846**	127.579**	616.625**
	(17.373)	(245.006)	(85.981)	(53.232)	(293.265)
Long Term Debt	-158.239**	91.196*	-77.792**	16.043	-155.599**
	(62.784)	(51.507)	(36.840)	(36.888)	(70.254)
Interest Expense	2.439**	2.737	1.135*	0.133	-1.299
	(1.057)	(1.957)	(0.679)	(1.052)	(2.294)
Market Implied Asset Value	-120.580	-723.788*	-167.131*	20.623	790.962**
	(105.095)	(379.644)	(95.250)	(247.021)	(397.574)
Implied Asset Volatility	0.001	-0.003***	0.001	-0.002***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Debt	108.138	-543.151**	87.264	-89.114	474.911*
	(151.854)	(237.670)	(70.596)	(105.124)	(280.176)
Market Value of Equity	-199.618*	-348.796	-222.691**	122.403	494.272
	(105.725)	(341.373)	(91.357)	(241.623)	(345.288)
Cost of Goods Sold	20.987***	-25.074*	17.373	-13.498	15.190
	(7.888)	(15.022)	(11.138)	(19.943)	(23.543)
Operating Expenses	23.448**	-27.039	21.595*	-20.743	8.149
	(9.270)	(16.468)	(11.872)	(21.193)	(25.479)
Inventory Costs	46.646	14.664	3.710	15.978	44.249
	(35.356)	(33.023)	(17.939)	(23.302)	(46.434)
Inventory Cost of Raw Materials	2.984	78.411**	6.278	27.465	-54.241*
	(16.909)	(33.320)	(7.753)	(17.031)	(31.541)
Net Profit	-6.200	39.881***	-7.296	53.882***	15.097
	(8.623)	(15.018)	(8.541)	(14.143)	(21.185)

*Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include fixed effects. The coefficeints and standard errors are rounded to the third decimal place. All values are winsorized using the full sample. All the standard errors are clustered using two way cluster at the industry-quarter level. Standard errors are presented in parenthesis. Column (1) reports the coeffieicents for low-risk firms in the Aichi Period (β_1). Column (2) reports the coefficeints of low-risk firms in the Post-Aichi period ($\beta_1 + \beta_3$). Column (3) reports the coefficeints for the high-risk firms in the Aichi period ($\beta_1 + \beta_2$). Finally, Column (4) represents the coefficeints for the high-risk firms in the post-Aichi period ($\beta_1 + \beta_2 + \beta_3 + \beta_4$). β_4 represents the coefficient of interaction of news shock $N_{t,g}$, risk quartile R_g and the time indicator $Post_t$. The variable $N_{t,q}$ is standardized. The Y variable is in real units. So the coefficients are interpretable as x natural unit change with respect to 1 standard-deviation rise in negative biodiversity news.β_4 captures the differential change in this effect between high- and low-risk firms across periods, i.e. how the divergence evolved in the post-Aichi period relative to the Aichi period. The standard errors of the linear combinations have been calculated using Wald t-test.*

Table D.3: Pooled Regression Results

The pooled regressions in Table D.3 highlight several significant shifts in firm behavior across the Aichi and post-Aichi periods. The interaction coefficients for probability of default and log volatility are both significant, indicating that the relative gap between high- and low-risk firms widened in the post-Aichi period. Translating the PD coefficient of 0.003 into credit spreads using Equation 1 implies a widening of about 18 basis points, showing that creditors now distinguish more aggressively between the two groups. Debt dynamics also reinforce this pattern: the interaction coefficient is positive and significant for short-term debt, negative and significant for long-term debt, and positive for total debt, suggesting that increases in high-risk firms' debt exposure in response to biodiversity news shocks were primarily driven by short-term borrowing and accompanied by a retrenchment from long-term borrowing. This points to a clear trend of maturity shortening. Finally, the significant negative interaction coefficient for inventory costs of raw materials indicates that the gap between high- and low-risk firms widened in the negative direction. Low-risk firms pre-emptively increased their raw material inventories, as seen in the significant positive post-Aichi coefficient, while high-risk firms made no significant adjustments, reflecting more cautious spending.