The Liquidity Cost of Biodiversity Risk:

Evidence from Equity and Corporate Bond Markets*

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Abstract

We investigate how firm-level biodiversity risk exposure affects secondary-market liquidity in equity and corporate bond markets. Using text-based and geographic risk metrics, we document a significant "liquidity tax" characterized by a sharp structural divergence: while biodiversity risk triggers modest increases in stock illiquidity, its impact is substantially more acute in the corporate bond market. We find that this deterioration is entirely mediated by an Institutional Participation Channel and an Investor Attention Channel. In the search-intensive, over-the-counter bond market, the systematic withdrawal of institutional capital and analyst monitoring creates an "informational vacuum" that forces dealers to widen bid-ask spreads. Conversely, the equity market exhibits significant resilience, with these channels providing only partial mediation. Finally, we show that the liquidity-enhancing effect of disclosure is *state-dependent*: while a negative disclosure tone facilitates liquidity by resolving uncertainty in steady-state, acute environmental shocks trigger a credit-risk signaling channel that overrides these benefits.

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1. Introduction

A central question in financial economics is how capital markets internalize complex, high-dimensional environmental risks. While a burgeoning literature examines the pricing of carbon transition risk (Pedersen 2026; Fuchs *et al.* Forthcoming), biodiversity loss represents a distinct and arguably more challenging phenomenon for financial intermediaries.[1] Unlike carbon emissions, which can be summarized by a single metric (tCO_2), biodiversity risk is characterized by extreme spatial heterogeneity, non-linear tipping points, and localized ecological dependencies (Giglio *et al.* 2026). Biodiversity-related services generate value in the tens of trillions of dollars (Costanza *et al.* 1997), while biodiversity loss is estimated to impose annual social and economic costs of US$4 trillion to US$20 trillion (Kapnick 2022). We investigate whether firm-level biodiversity risk exposure affects secondary-market quality —a key determinant of trading frictions, risk sharing, and the speed of price discovery—focusing on the distinct liquidity dynamics across equity and corporate bond markets.[2]

Our analysis is motivated by a fundamental theoretical "tug-of-war" regarding the role of environmental disclosure. On one hand, nature-related disclosures may facilitate an *Information Resolution Channel*. In this view, transforming "Knightian uncertainty" into priceable risk reduces information asymmetry between informed and uninformed traders, thereby improving market depth (Diamond & Verrecchia 1991). On the other hand, for assets with concave payoff structures—such as corporate bonds—disclosures of biodiversity liabilities may trigger a *Credit Risk Signaling Channel*. Under this mechanism, the revelation of tail risks leads to a defensive withdrawal by market participants, particularly in dealer-intermediated markets where inventory-holding costs are sensitive to solvency shocks (Nagel 2012). By examining both asset classes simultaneously, we provide a unique laboratory to adjudicate these competing forces.

[1] https://deloitte.wsj.com/sustainable-business/making-nature-and-biodiversity-a-business-agenda-priority-5b537795

[2] We focus on liquidity in the stock and bond markets as it is a key characteristic of market quality and plays an important role in reducing firm-specific default risk (Brogaard *et al.* 2017; Nadarajah *et al.* 2021), lowering the cost of capital (Fang *et al.* 2009), and mitigating managerial short-termism (Chen *et al.* 2015).

We construct a multidimensional suite of biodiversity risk exposure metrics using firm-level biodiversity risk exposure measures developed by Giglio *et al.* (2026). These include presence-based scores, regulation-specific exposure, and a sentiment-based measure. Our baseline results reveal a significant "liquidity tax" associated with biodiversity risk: firms with higher exposure exhibit substantially higher illiquidity. Crucially, we document a structural divergence in this response. While equity liquidity declines modestly, the effects are substantially stronger and more persistent in corporate bond markets. This pattern is consistent with the greater sensitivity of decentralized, dealer-intermediated Over-the-Counter (OTC) markets to changes in investor participation and inventory risk (Li and Yu (2026); Dick-Nielsen *et al.* (2012)).

The role of disclosure tone provides a critical refinement to this finding. In a cross-sectional "steady-state," we find that a negative biodiversity tone is actually associated with lower illiquidity in both markets. This result suggests that in a "steady-state" equilibrium, the *Information Resolution Channel* generally dominates; even "bad news" improves market quality if it reduces valuation uncertainty (Diamond & Verrecchia 1991) and prevents the "lemons problem" typical of opaque, non-standardized risks (Akerlof 1970). By explicitly discussing biodiversity-related risks in a negative tone, managers provide "hard information" (Liberti & Petersen 2019) that allows market participants to price the risk accurately, thereby mitigating trading frictions. This is consistent with evidence that corporate disclosures—even those containing adverse information—can facilitate liquidity by reducing the information-processing costs for outside investors (Lang and Lundholm (2000);Muslu *et al.* (2015)). In this regime, transparency acts as a lubricant for market quality by providing the "price-relevant" clarity necessary for efficient trading. Our findings are robust across a range of alternative specifications and identification strategies. In particular, the results hold using alternative measures of liquidity and biodiversity exposure, including an independent geographic proxy that is not based on firm disclosures.

However, we document that this relationship fundamentally shifts during periods of acute environmental crisis. Exploiting the 2010 Deepwater Horizon (DWH) oil spill as a quasi-exogenous shock to the perceived importance of nature-related liabilities and utilizing a difference-in-differences (DID) framework, we document a stark divergence in market resilience that reveals a fundamental "regime shift" in the pricing of environmental risk. While equity market liquidity remains largely unaffected, corporate bond liquidity for biodiversity-intensive firms deteriorates significantly following the spill. This bifurcation suggests that during an acute crisis, the *Credit Risk Signaling Channel* overrides the benefits of transparency. In the face of systemic biodiversity-related shocks, the decentralized and dealer-intermediated architecture of the bond market becomes a source of fragility; bond dealers, sensitive to the potential for catastrophic tail-risk and collateral impairment, appears to view biodiversity-exposed assets as "toxic inventory" (Nagel 2012). This leads to a defensive withdrawal of liquidity provision that is absent in the more transparent, centralized equity market. Our results imply that while the negative tone of biodiversity-related disclosure may resolve uncertainty in "steady-state" periods, it may paradoxically exacerbate illiquidity during periods of high environmental salience by providing a clearer signal of potential insolvency to risk-averse intermediaries.

Finally, we identify the structural mechanisms driving these liquidity dynamics by adjudicating between the *Institutional Participation Channel* and the *Information Production and Attention Channel*. Following the theory of limited market participation (Merton 1987), we document a sharp structural divergence in how biodiversity risk shapes the investor base. In the corporate bond market, the relationship between biodiversity exposure and illiquidity is entirely mediated by a systematic "institutional exit." Because the decentralized OTC bond market relies on a concentrated group of sophisticated intermediaries to provide "patient" capital (Starks *et al.* 2026), their withdrawal creates a first-order participation friction. When these key participants exit, the remaining bond dealers face a more "toxic" or asymmetric order flow and must widen bid-ask spreads to protect against heightened

inventory risk (Nagel 2012). In contrast, the equity market exhibits only partial mediation, as the centralized architecture and diverse participant base provide a "liquidity floor" that buffers against the exit of sophisticated institutions.

In tandem, we find that the high-dimensional complexity of nature-related signals imposes a "complexity tax" on information intermediaries, leading to a contraction in the private production of information. In the bond market, biodiversity risk exposure functions as a potent driver of information attrition, where a contraction in analyst coverage serves as the primary causal conduit for illiquidity. This "informational vacuum" exacerbates search costs and adverse selection, as the absence of a "research anchor" (Kwan *et al.* 2026) forces dealers to price the resulting opacity as a liquidity friction. Conversely, we find that the equity market's information environment is significantly more resilient; equity analysts—incentivized by the non-linear upside of firm value—continue to provide coverage despite the high cost of decoding specialized biodiversity signals. Notably, while raw exposure triggers a retreat in monitoring, a negative biodiversity-related disclosure tone acts as a clarifying signal that attracts analyst scrutiny and mitigates attention constraints in both markets. Collectively, these results demonstrate that biodiversity risk impairs market quality primarily by shifting the search-intensive bond market into a low-liquidity equilibrium characterized by the dual attrition of trading capital and private information.

This paper makes three primary contributions to the literature. First, we extend the burgeoning field of biodiversity finance (e.g., Chen et al. 2023; Garel et al. 2024; Coqueret et al. 2025; Giglio et al. 2026) by documenting that nature-related risks are not merely priced in long-run returns, but manifest as first-order secondary-market trading frictions. We are the first to provide a comprehensive cross-asset analysis, showing that the "liquidity tax" of nature-dependency is a first-order concern for investors.

Second, we contribute to the market microstructure literature by identifying biodiversity risk as a novel source of participation and attention frictions. Our analysis demonstrates how high-

dimensional environmental risks interact with specific market architectures. Specifically, the contrast between centralized equity exchanges and decentralized bond markets reveals that biodiversity risk imposes a structural "participation barrier" on dealer-intermediated markets—a friction that standard, aggregate ESG metrics fail to capture.

Third, we provide a critical refinement to the disclosure literature**.** Through an adjudication between the *Information Resolution* and *Credit Risk Signaling* channels, we show that the impact of environmental disclosure is fundamentally state-dependent. While an explicit negative tone improves liquidity in the cross-section by resolving valuation uncertainty, it triggers a defensive withdrawal during systemic shocks by signaling potential insolvency. This has direct implications for the design of global biodiversity reporting frameworks.

The remainder of the paper proceeds as follows. Section 2 develops our theoretical framework and hypotheses. Section 3 describes the data and variable construction. Section 4 presents the empirical design. Section 5 reports baseline results, robustness tests and identification strategies. Section 6 studies the underlying mechanisms. Section 7 concludes.

2. Theoretical Framework and Hypotheses Development

In this section, we develop a theoretical framework to examine how the unique characteristics of biodiversity risk—specifically its high-dimensional complexity and the absence of standardized metrics—interact with market microstructure to influence secondary-market liquidity. We move beyond the traditional "preference-based" view of ESG investing to focus on the informational frictions and participation constraints that arise when sophisticated intermediaries process non-linear nature-related signals. By distinguishing between the centralized architecture of equity markets and the search-intensive nature of OTC bond markets, we derive testable hypotheses regarding the displacement of institutional capital, the attrition of private information production, and the state-dependent role of disclosure sentiment.

2.1. Biodiversity Risk as a Financial Friction

A growing literature in finance examines the pricing of biodiversity risk in primary and secondary markets, providing evidence for the emergence of a "nature risk premium." Recent studies utilize text-based measures of corporate disclosure to show that biodiversity exposure is reflected in wider corporate bond spreads (Chen *et al.* (2023); Cherief *et al.* (2022)), higher bank loan rates and reduced credit availability (Becker *et al.* (2025); Nguyen *et al.* (2025)), as well as increased audit and monitoring costs (Hudson 2024; Steindl *et al.* 2025). Some other studies develop firm-level measures of biodiversity exposure based on corporate disclosures and show that biodiversity risk is reflected in equity and bond prices (Giglio *et al.* (2026); Ma *et al.* (2024); Xiong (2023); Garel *et al.* (2024)).

While this literature establishes that biodiversity risk is a first-order concern for valuation and capital allocation, it focuses primarily on price levels and primary-market outcomes. Much less is known about how biodiversity risk affects secondary-market trading dynamics, including liquidity, participation, and transaction costs, once securities are issued. Secondary-market liquidity is a critical dimension of market quality, influencing risk-sharing, price discovery, and the real investment decisions of firms (Amihud and Mendelson (1986), Fang *et al.* (2009), Brogaard *et al.* (2017)). Glosten and Milgrom (1985) show that liquidity is determined by the interplay of investor participation, information asymmetry, and the inventory costs of intermediaries. Biodiversity risk introduces unique frictions into this framework. Unlike carbon risk, which can often be distilled into a single metric (CO2 emissions), biodiversity risk is spatially heterogeneous, non-linear, and embedded in opaque global supply chains, and subject to evolving regulatory interpretation, all of which increase information-processing costs for investors and intermediaries (Giglio et al. 2026; Garel et al. 2024).

These features suggest that biodiversity risk functions as a high-dimensional informational friction. On one hand, the complexity of nature-related dependencies may increase the marginal cost of information processing, discouraging investor participation and widening bid-ask spreads. On the other hand, the increasing salience of these risks could trigger portfolio rebalancing and risk-sharing

trades, potentially enhancing trading volume (Baker & Stein 2004). Whether biodiversity risk ultimately impairs or improves market quality is therefore an empirical question that likely depends on the structural differences between centralized equity exchanges and decentralized OTC bond markets.

Hypothesis 1 (Net Liquidity Impact)*: Firm-level biodiversity risk exposure significantly affects secondary-market liquidity, with the direction and magnitude of the effect contingent on the prevailing asset-class-specific frictions*.

2.2. The Institutional Participation Channel

The first primary mechanism through which biodiversity risk translates into market illiquidity operates through the composition and participation of the investor base. Institutional investors—including pension funds, mutual funds, and insurance companies—function as the foundational suppliers of stable, information-intermediated capital in modern financial markets. We posit that biodiversity risk acts as a structural barrier to entry for these sophisticated intermediaries, triggering a systematic withdrawal that impairs market depth.

This mechanism is grounded in the theory of limited market participation (Merton 1987). When a specific risk is perceived as unquantifiable, idiosyncratic, or subject to high monitoring costs, sophisticated investors may opt to "vote with their feet" and divest rather than bear the ongoing costs of risk assessment (Dyck *et al.* 2019). In the context of biodiversity, the lack of standardized metrics and the reliance on qualitative, spatially heterogeneous disclosures impose significant "auditing costs" on institutions. If these costs exceed the marginal benefit of holding the security, a systematic exit occurs.

The impact of this institutional withdrawal is highly dependent on the microstructure of the asset class. In corporate bond markets, liquidity is fundamentally determined by a concentrated group of institutional players and decentralized dealer networks (Li & Yu 2026). Because bond trading is

search-intensive and lacks the centralized matching of equity exchanges, the presence of stable, "natural" institutional buyers is critical. When institutions exit, the "liquidity supply" is truncated. Dealers, facing a more "toxic" or asymmetric order flow in the absence of sophisticated counterparties, must widen bid-ask spreads and reduce quote depth to protect against inventory risk ((Nagel 2012); (Dick-Nielsen *et al.* 2012)).

In contrast, equity markets benefit from a more diverse participant base. While the exit of institutions removes a layer of sophisticated monitoring, the centralized nature of equity trading and the presence of high-frequency traders or retail participants may provide a "liquidity floor" that is absent in debt markets. However, as noted by Starks *et al.* (2026), the displacement of long-horizon institutional investors can still lead to increased price volatility and a higher liquidity premium. Therefore, we posit that while both markets suffer from reduced participation, the participation-mediated illiquidity will be significantly more severe in corporate bonds due to the structural reliance of the OTC market on institutional intermediation.

Hypothesis 2a (The Institutional Participation Channel): *Biodiversity risk exposure impairs market liquidity through the systematic withdrawal of sophisticated institutional investors. This channel is the dominant driver of illiquidity in corporate bond markets, where trading costs are more sensitive to the exit of stable, information-intermediated capital.*

2.3. The Information Production and Attention Channel

An alternative, though non-mutually exclusive, mechanism through which biodiversity risk impairs liquidity is the Information Production and Attention Channel. This channel focuses on the supply-side frictions of the informational environment. Following the theories of limited attention (Peng and Xiong (2006)), we argue that the high-dimensional and non-standardized nature of biodiversity disclosure imposes a "complexity tax" on information intermediaries, leading to a contraction in the private production of information.

The core of this friction lies in the cognitive and resource constraints of market participants. As highlighted by Kwan *et al.* (2026), institutional attention is a scarce resource that is allocated based on the value-relevance of news. Biodiversity risk—characterized by spatial heterogeneity and opaque regulatory implications—requires specialized expertise to decode (Giglio *et al.* 2026). In a competitive market for information, analysts and investors face an optimization problem: the marginal cost of processing these complex, non-linear signals must be weighed against the expected benefit of the resulting coverage. If the "complexity tax" of biodiversity-related exposure is too high, intermediaries may rationally shift their attention toward more standardized, lower-cost signals (e.g., traditional financial metrics or carbon emissions), leading to information attrition.

This retreat of information intermediaries has profound implications for secondary-market liquidity. In the absence of robust analyst coverage and public monitoring, the informational environment becomes sparse, increasing search costs and adverse selection risk (Merton 1987). When private information production declines, the "common knowledge" that anchors trading disappears, forcing market participants to demand a higher liquidity premium to compensate for the risk of trading against better-informed counterparties.

The impact of this "informational vacuum" is particularly severe in the decentralized corporate bond market. Unlike equity markets, where price discovery is aided by centralized limit order books and high-frequency data, bond markets rely on search-based intermediation. As noted by Kwan *et al.* (2026), when institutional attention to a specific security wanes, the value-add of that position to the portfolio diminishes, often leading to reduced trading activity. In an OTC setting, if analysts stop providing the "research anchor" for a firm's nature-related liabilities, dealers face higher uncertainty regarding the "fair value" of the bonds. To protect against this opacity, dealers widen bid-ask spreads, effectively pricing the lack of attention as a liquidity friction.

Hypothesis 2b (The Information Production and Attention Channel): *Biodiversity risk exposure impairs market liquidity by increasing the information-processing burden on investors and*

intermediaries. This information attrition generates more pronounced liquidity frictions in corporate bonds than in equities due to the search-intensive nature of OTC trading.

2.4. The Information Resolution vs. Credit Risk Signalling Channels

While the mere presence of biodiversity risk exposure introduces structural frictions, the qualitative content and sentiment of corporate communication may serve to either exacerbate or mitigate these effects. We posit that the impact of disclosure sentiment is filtered through the specific payoff profiles of equity and debt, potentially triggering two competing economic mechanisms.

In the equity market, the primary barrier to liquidity is often an "asymmetric information bottleneck." When firms are silent about complex risks like biodiversity, investors may assume the worst or face high search costs to uncover hidden liabilities. Consequently, uninformed investors may protect themselves by withdrawing from the market or demanding high lemons-premiums. According to the foundational disclosure logic of Diamond and Verrecchia (1991), the revelation of information—even if the news is fundamentally "bad"—can improve market quality by reducing the variance of beliefs between informed and uninformed traders. By explicitly discussing nature-related risks in a negative tone, managers provide "hard information" regarding potential liabilities and mitigation strategies. This *Information Resolution Channel* suggests that transparency resolves fundamental uncertainty, thereby lowering the "lemons premium" and facilitating trading activity among participants who previously avoided the security due to its high opacity.

In corporate bond markets, however, the theoretical prediction is ex ante ambiguous due to the concave payoff structure of debt. We identify two competing channels: the *Information Resolution Channel* and the *Credit Risk Signalling Channel*. On one hand, the *Information Resolution Channel* suggests that biodiversity risk is characterized by high levels of 'opacity' and 'Knightian uncertainty.' Because the secondary bond market is decentralized and dealer-intermediated, dealers may widen spreads to protect against the 'unknown unknowns' of a firm’s nature-dependency. In this setting, a

negative disclosure tone serves as a commitment to transparency. By explicitly quantifying potential liabilities, firms allow dealers to transition from a state of ambiguity to one of priceable risk, thereby reducing the adverse selection component of the bid-ask spread and improving liquidity.

Conversely, the *Credit Risk Signaling Channel* posits the information-processing logic is governed by the concave payoff structure of debt. Bondholders do not share in the "upside" of nature-positive transitions but are fully exposed to the "downside" of nature-related defaults or regulatory fines. Consequently, bond investors and over-the-counter (OTC) dealers do not view negative disclosure as a clarifying signal that resolves ambiguity. Instead, they perceive negative sentiment as a fundamental information shock to the firm's solvency. In the decentralized bond market, such a shock triggers a defensive response from dealers. To protect against the heightened inventory risk associated with a deteriorating credit profile, dealers widen bid-ask spreads and reduce quote depth, thereby impairing liquidity.

Whether negative biodiversity disclosure improves or impairs bond liquidity is therefore an empirical question that depends on whether the benefit of uncertainty resolution outweighs the cost of downside risk signalling.

Hypothesis 3 (The Information Resolution Channel): *Conditional on biodiversity risk exposure, negative exposure tone improves secondary-market liquidity in equity markets by resolving valuation uncertainty. However, the direction of this effect on the bond markets depends on the relative dominance of uncertainty resolution versus credit risk signalling.*

3. Data, sample and variables construction

3.1.Stock market data

We obtain daily stock-level trading data from the Center for Research on Security Prices (CRSP) to construct stock liquidity measures. Our sample includes all U.S.-based common stocks (CRSP share codes 10 and 11) listed on the New York Stock Exchange (NYSE), the American Stock Exchange

(AMEX), and NASDAQ over the period from January 2001 to December 2022. We exclude observations with non-positive prices and missing returns. To mitigate the impact of stale prices and spurious trading volume, we follow Nyborg and Wang (2021) and remove observations with positive trading volume but missing closing prices either on the trading day or on the previous trading day. After merging with Compustat and applying these filters, the final stock sample consists of 3,216 firms for which we compute liquidity measures.

3.2.Corporate bond data

We obtain monthly U.S. corporate bond data from the WRDS Bond Returns database, which provides cleaned and standardized bond-level information suitable for empirical research. The database combines transaction-level data from FINRA's Trade Reporting and Compliance Engine (TRACE) with bond characteristics from the Mergent Fixed Income Securities Database (FISD). Data cleaning follows the procedures outlined in Dick-Nielsen (2014).

The bond-level data include price (*PRICE_EOM*), returns (*RET_EOM*), spread (*T_SPREAD*), and bond characteristics such as offering amount (*Offering Amount*), coupon rate (*Coupon*), time to maturity (*TMT*), credit rating (*Credit Rating*). We restrict the sample to non-municipal corporate bonds classified as convertible bonds, debentures, medium-term notes (MTNs), and MTN zero-coupon bonds, including secured, senior, and subordinated issues.

The raw WRDS Bond Returns database covers the period from July 2002 to December 2023. However, because firm-level biodiversity risk exposure measures are only available through December 2022, we restrict the corporate bond sample to the period from July 2002 to December 2022 to maintain consistency across datasets. The final bond sample comprises 12,972 bonds issued by 1,287 firms.

3.3.Biodiversity risk exposure data

We measure firm-level biodiversity exposure using the Biodiversity Scores dataset developed by Giglio *et al.* (2026), hereafter referred to as GKSZ Biodiversity Scores. The dataset applies natural

language processing to firms' annual 10-K filings to identify and classify biodiversity-related disclosure. Specifically, biodiversity-related sentences are identified using predefined regular expressions and then classified using a BERT-based model into positive, neutral, or negative sentiment categories. Based on these classifications, the dataset provides several firm-year measures capturing the presence, regulatory relevance, and tone of biodiversity-related discussion in corporate disclosures.

3.4.Biodiversity Risk Exposure Indicators

Following Giglio et al. (2026), we construct three firm-year indicators of biodiversity risk exposure. *Count_Score* captures the presence of biodiversity-related discussion in a firm's 10-K filing. The indicator equals one if the filing contains at least two biodiversity-related sentences and zero otherwise. This measure reflects the presence of biodiversity-related exposure but does not distinguish between risk- and opportunity-oriented discussion. *Reg_Score* captures biodiversity exposure associated with biodiversity-related regulatory risk. This indicator equals one if the firm's 10-K contains at least two biodiversity-related sentences and at least one reference to biodiversity-related regulatory terms such as *law*, *regulation*, *Act*, *ESA*, *discharge*, or *restriction*. *Neg_Score* captures the tone of biodiversity-related disclosure. The underlying sentiment score is defined as the difference between the number of negative and positive biodiversity-related sentences identified in the firm's 10-K filing using a BERT-based classifier, following Giglio et al. (2026). In our study, *Neg_Score* is an indicator equal to one when the net tone of biodiversity-related discussion is negative, and zero otherwise. This measure captures whether a firm's biodiversity-related disclosure is tilted toward adverse or risk-oriented content. Firm-years with no biodiversity-related discussion or only neutral statements receive a score of zero.

These binary indicators classify firms according to whether they are exposed to biodiversity-related risks in a given year and follow the empirical convention adopted in the biodiversity finance literature.

3.5.Financial characteristics data

We obtain firm-level financial characteristics from Compustat. Specifically, we extract firm size, asset tangibility, R&D intensity, advertising intensity, debt ratio, and leverage. Data on the number of analysts following a firm are obtained from the Institutional Brokers' Estimate System (I/E/E/S) database. Data on institutional ownership are sourced from the Thomson-Reuters Institutional (13F) Holdings database. The study's sample period covers 2001 to 2022. Detailed variable definitions are provided in Appendix A.

3.6.Variables measurement

3.6.1. Measures of stock liquidity

To measure equity market liquidity, we employ the Amihud (2002) illiquidity measure as our primary proxy. The Amihud measure captures the price impact of trading and is widely used in the finance literature as an indicator of trading frictions and market depth.

Following Amihud (2002), we measure stock illiquidity using the price-impact proxy constructed from daily CRSP data (variables *ret*, *prc*, and *vol*). For firm *i* in fiscal year *t*, the Amihud illiquidity measure is defined as

$$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{| R_{i,d} |}{DollarVolume_{i,d}},$$

where $R_{i,d}$ denotes the daily stock return, $DollarVolume_{i,d}$ represents the dollar trading volume on day d, and $D_{i,t}$ is the number of trading days for firm i in fiscal year t. Consistent with the CRSP data structure, daily dollar trading volume is computed as $prc \times vol$, and the Amihud ratio is scaled by $1{,}000{,}000$ following the standard convention in the literature. Stock returns are adjusted for delisting following Bali *et al.* (2016). To address the double-counting of trading volume for NASDAQ stocks, reported dollar trading volume is halved (see Nyborg & Wang 2021). The daily Amihud ratios are then averaged over the firm's fiscal year to obtain an annual measure of price impact. Because the

distribution of the Amihud measure is highly skewed (Edmans *et al.* (2013), Marks and Shang (2024)), we transform the variable using the natural logarithm of one plus the Amihud illiquidity ratio. This transformed measure is denoted *IlliqAM*. Higher values of the Amihud measure indicate greater price impact per unit of trading volume and therefore lower market liquidity.

To ensure that our findings are not driven by a particular liquidity proxy, we also consider two alternative proxies for stock illiquidity. The first is the cost-per-price measure proposed by Fong *et al.* (2017), which estimates effective transaction costs using daily return and volume data. The second is the proportion of zero-return trading days during the firm's fiscal year, following Lesmond *et al.* (1999). We denote these two alternative measures as *IlliqFHT* and *IlliqZeros*, respectively.

3.6.2. Measures of corporate bond liquidity

Corporate bond liquidity is measured using transaction-level data from the TRACE database. Because corporate bonds trade in decentralized over-the-counter markets where dealer intermediation plays a central role, liquidity is typically assessed using measures that capture transaction costs and price dispersion rather than trading volume alone.

Our primary measure of bond illiquidity is the round-trip transaction cost estimator proposed by Feldhütter (2012). Following this approach, we compute round-trip trading costs using transaction prices observed in TRACE. For each bond, the round-trip transaction cost is calculated as twice the difference between the lowest and highest transaction prices observed within a trading round trip during the quarter. To express the measure as a relative spread, the round-trip transaction cost is scaled by the average of the maximum and minimum transaction prices. Price information is obtained from the WRDS Bond Return database (variable *PRICE_EOM*). This procedure yields a quarterly round-trip transaction cost measure (*TC_Roundtrip*) for each bond. We then compute an annual measure by averaging the quarterly transaction cost estimates within each fiscal year. Higher values of this measure indicate larger trading costs and, therefore, lower bond market liquidity. To reduce the influence of

extreme values, we transform the measure using the natural logarithm of one plus the round-trip transaction cost ratio. The resulting variable is denoted *IlliqRT.*

As alternative measures for a robustness check, we also consider two alternative measures of bond illiquidity. The first is the Roll spread estimator based on Dick-Nielsen *et al.* (2012). We employed a modified intra-month version of Dick-Nielsen et al.'s (2012) Roll estimator for effective spreads using the end-of-month bond return from the WRDS bond return (variable *RET_EOM*). The Roll estimator captures the effective bid-ask spread through the negative autocovariance of transaction prices induced by bid-ask bounce. Monthly estimates are aggregated at the bond level by taking the annual median of the monthly Roll estimates. Because higher Roll spreads correspond to larger bid-ask spreads and therefore lower liquidity, we again apply a logarithmic transformation and denote the resulting variable *IlliqROLL.* Finally, we employ the interquartile price range measure introduced in Schestag et al. (2016), which captures liquidity through the dispersion of transaction prices. This measure is computed as the difference between the 75^{th} and 25^{th} percentiles of transaction prices relative to the average price. We standardize this measure using the natural logarithm transformation and denote it *IlliqIQR*.

3.7.Summary statistics

Table 1 provides summary statistics for the main variables used in the empirical analysis. Panel A presents statistics for the stock sample at the firm–year level, while Panel B reports statistics for the bond sample at the bond–issuer–year level. The final dataset contains 35,787 firm-year observations for equities and 67,414 bond-issuer-year observations. The primary dependent variables are the Amihud (2002) stock illiquidity measure (*IlliqAM*) and the round-trip bond transaction cost measure (*IlliqRT*). The key explanatory variables are three indicators capturing biodiversity risk exposure derived from firms' 10-K disclosures: *Count_Score, Reg_Score,* and *Neg_Score*. Firm-level control variables are obtained from Compustat and therefore cover slightly fewer observations. In the bond

sample, issuer-level controls include firm size measured by the logarithm of market capitalization (*log*(MCAP)) and profitability measured by return on assets (*ROA*).

[**Insert Table 1 about here**]

Panel A of Table 1 shows that stock illiquidity exhibits substantial cross-sectional variation. The mean value of *IlliqAM* is 0.186, while the median is 0.004, indicating that the distribution is skewed toward larger values. The interquartile range spans 0.001 to 0.046, suggesting considerable heterogeneity in trading frictions across firms.

Biodiversity exposure is common in the equity sample. The *Count_Score* indicator equals one in 42.3% of firm–year observations, while *Reg_Score* equals one in 41.6% of observations. The *Neg_Score* indicator is more frequent, taking the value one in 58.9% of firm–years. Because these variables are binary indicators, the values correspond to the proportion of firms whose 10-K disclosures contain biodiversity-related exposure signals for each metric.

The firm characteristics are broadly consistent with large publicly traded U.S. firms. The mean value of log(*MCAP)* is 13.633, indicating relatively large market capitalization. The median book-to-market ratio (*logMB*) is 1.176, while stock return volatility (*log*(Std_Ret)) averages −3.575. Analyst coverage (*ln_Analysts*) averages 2.606, corresponding to roughly three analysts following each firm. Institutional ownership (*Total_IO*) averages 38%, while investment intensity (*CAPXAT*) averages 0.043 of total assets. Profitability (*ROA*) averages 0.025, with a median of 0.087, indicating moderate variation in firm performance across the sample.

Panel B of Table 1 reports summary statistics for the corporate bond sample. Bond trading costs are economically meaningful and display substantial dispersion. The mean round-trip transaction cost (*IlliqRT*) is 1.634, with a median of 1.615 and an interquartile range of 1.068 to 2.140, indicating significant heterogeneity in bond market liquidity across issuers.

Biodiversity exposure rates in the bond sample are broadly comparable to those observed in the equity sample. *Count_Score* equals one in 38.8% of observations, and *Reg_Score* equals one in

37.2% of observations. The negative-tone indicator *Neg_Score* appears in 66.4% of bond–issuer–year observations. These figures indicate that biodiversity-related disclosures with a net negative tone are relatively prevalent among firms issuing corporate bonds.

The bond characteristics reflect typical features of U.S. corporate debt issues. The median offering size is $0.500 million (mean $0.637 million), and the average coupon rate is 5.16%. Bonds have an average maturity of 13.78 years (median 10 years) and a median age of three years. The average credit rating is 15.68, corresponding approximately to investment-grade ratings. For observations with available issuer financial data, the median log(*MCAP*) is 10.383, and the median ROA is 0.104.

Table 2 reports industry-level averages of firms' 10-K biodiversity scores across the Fama-French 38 industry classification. The results indicate substantial cross-industry variation in biodiversity-related disclosures. Industries directly linked to natural resources—such as agriculture, forestry, and fishing—exhibit the highest biodiversity exposure, with both *Count_Score* and *Reg_Score* equal to one. More broadly, the *Neg_Score* indicator is relatively high across many industries, often exceeding 0.60, suggesting that biodiversity-related discussion in corporate disclosures is frequently framed in a risk-oriented or adverse tone.

[**Insert Table 2 about here**]

4. Methodology

This section presents the empirical design used to examine the relation between firm-level biodiversity risk exposure and secondary-market liquidity in equity and corporate bond markets. To test *Hypothesis 1*, we estimate panel regressions that relate firm-level biodiversity risk exposure to measures of secondary-market liquidity in the equity and corporate bond markets.

For equities, we estimate the following specification:

$$Liquidity_{it} = \alpha + \beta Biodiversity\ Risk\ Exposure_{it} + \gamma' X_{it} + \delta_{kt} + \theta_i + \varepsilon_{it} \quad (1)$$

where i, k, and t denote firm, industry, and years, respectively. $Liquidity$ denotes an alternative proxy of stock liquidity– *IlliqAM*, *IlliqFHT* and *IlliqZeros* – for firm i in year t. $Biodiversity\ Risk\ Exposure$ is an indicator for firm-level biodiversity risk exposure (i.e., *Count_Score*, *Neg_Score*, *Reg_Score*) for firm i in year t. X indicates lagged firm-level controls, including the log of market capitalisation (*log(MCAP)*), the log of market-to-book value (*log(MB)*), the log of stock return volatility (*log(Std_Ret)*), the number of analysts following (*ln_Analysts*), institutional ownership (*Total_IO*), the inverse of stock price (*1/Price*), capital expenditure (*CAPXAT*), and return on assets (*ROA*). To absorb potential confounding factors, we include firm fixed effects (θ_i) to control for time-invariant firm characteristics, such as business models, geographic exposure, and baseline disclosure practices. We further include industry-by-year fixed effects (δ_{kt}) based on the Fama-French 38-industry classification. These effects account for time-varying shocks common to all firms within a sector, such as sector-specific regulatory developments or shifts in commodity prices. Standard errors are clustered at the firm level and $\varepsilon_{i,t}$ is the error term.

For corporate bonds, we estimate a bond-level specification:

$$Bond\ Liquidity_{jit} = \alpha + \beta Biodiversity\ Risk\ Exposure_{it} + \partial' W_{jt} +$$

$$+\gamma' Z_{it} + \delta_i + \theta_{kt} + \varepsilon_{jit} \quad (2)$$

where j, i, k, and t denote bond, firm, industry, and year, respectively. $Bond\ Liquidity$ denotes bond-level illiquidity – *IlliqRT*, *IlliqROLL*, and *IlliqIQR* – for bond j issued by firm i in year t. $Biodiversity\ Risk\ Exposure$ is an indicator for firm-level biodiversity risk exposure (i.e., *Count_Score*, *Neg_Score*, *Reg_Score*), which captures whether firm i issuing bond j is exposed to biodiversity-related risks in year t. W includes bond characteristics, such as offering amount, coupon rate, maturity, maturity squared, credit rating and bond age. Z indicates firm-level controls, including the natural log of market capitalization (*log(MCAP)*) and ROA. We maintain the same fixed-effects structure as the equity analysis, with standard errors clustered at the bond level.

A primary empirical challenge in our setting is the potential for selection bias; firms that choose to disclose biodiversity risks may systematically differ from non-disclosing firms along dimensions that independently affect liquidity. To ensure that our estimates capture the marginal effect of biodiversity risk rather than latent firm-level differences, we employ entropy balancing procedure to construct a weighted benchmark sample of non-exposed firms that matches the distribution of observable characteristics of biodiversity-exposed firms (see Hu *et al.* 2025). In all regression analyses, observations are weighted by the entropy-balancing weights, so that estimated liquidity differences are not driven by imbalances in observable firm characteristics between exposed and non-exposed firms.

5. Empirical results and discussions

This section evaluates the impact of firm-level biodiversity risk exposure on secondary-market liquidity. We first establish baseline associations across equity and corporate bond markets, testing the competing effects of risk exposure versus disclosure tone (Hypothesis 1). We then subject these findings to a battery of robustness checks, including alternative liquidity proxies and a geographic measure of physical biodiversity exposure. Finally, we address identification concerns using an Impact Threshold for Confounding Variables (ITCV) analysis and a Difference-in-Differences (DID) framework centered on the 2010 Deepwater Horizon (DWH) oil spill.

5.1. Baseline Results: Biodiversity Risk and Liquidity

Using the empirical specifications detailed in Section 4 and entropy-balanced samples, we estimate panel regressions relating firm-level biodiversity risk exposure to standardized measures of stock and bond illiquidity. The analysis is conducted separately for equities and corporate bonds to accommodate the fundamental differences in their respective trading environments and market architectures.

5.1.1. Equity Markets

Panel A of Table 3 reports results of the regression Equation (1) for the stock sample. Our primary dependent variable is the natural logarithm of the Amihud (2002) illiquidity ratio (*IlliqAM*). Across all specifications, firms with high biodiversity exposure, measured by *Count_Score* and *Reg_Score*, exhibit significantly higher illiquidity than non-exposed firms (columns 1and 3). These effects remain statistically significant after controlling for firm size, valuation, volatility, analyst coverage, institutional ownership, price level, investment intensity, and profitability (columns 2and 4).

The economic magnitude of these effects is economically substantial. Based on column (2), stock illiquidity is approximately 13.8% higher for firms with biodiversity risk exposure as measured by the *Count_Score*[3]. We observe a similar magnitude for regulation-related exposure *Reg_Score* in column (4). These results suggest that biodiversity risk acts as a significant source of information asymmetry in equity markets, likely increasing the "lemons premium" demanded by uninformed traders who fear hidden environmental liabilities.

However, the results for *Neg_Score* (columns 5–6) reveal a significant countervailing effect. Conditional on being exposed, firms that use a more negative tone in their biodiversity-related disclosures experience approximately 4% lower stock illiquidity.[4] This supports our *Information Resolution Channel (Hypothesis 3)*: in the equity market, "bad news is better than no news." Explicitly documenting potential biodiversity liabilities provides "hard information" that resolves fundamental valuation uncertainty, thereby narrowing the information gap between informed and uninformed traders and improving market depth.

The control variables behave as expected. Larger firms, firms with higher analyst coverage, and more profitable firms exhibit greater stock liquidity, consistent with established evidence in the liquidity literature (Gopalan *et al.* 2012; Marks & Shang 2024). Thus, while biodiversity exposure is

[3] i.e., $exp(0.129) - 1$

[4] In column (5), stock illiquidity declines on average by approximately 3.6% for biodiversity-exposed firms whose disclosures convey negative sentiment about biodiversity risk (i.e., $\exp(-0.049) - 1$).

associated with reduced stock liquidity on average, biodiversity-related tone is systematically related to cross-sectional variation in liquidity outcomes among exposed firms.

[**Insert Table 3 about here**]

5.1.2. Corporate Bond Markets

Panel B of Table 3 presents corresponding results for corporate bond markets, where liquidity is measured using round-trip trading costs (*IllqRT*).[5] As in the equity analysis, all specifications include firm fixed effects and industry-year fixed effects, with columns (2), (4), and (6) additionally controlling for bond characteristics.

The bond market reveals a liquidity response to biodiversity risk that is both statistically more robust and economically larger than that observed in equities. In columns (2) and (4), the estimated coefficients on *Count_Score* and *Reg_Score* imply that biodiversity-exposed firms experience an increase in round-trip trading costs of approximately 4.1% to 4.7% relative to non-exposed peers.[6] This heightened sensitivity in the fixed-income market is consistent with the nature of biodiversity risk as a "downside" or "tail risk." While equity investors may price in potential upside from green innovation, bondholders—whose payoffs are concave—are primarily concerned with the increased probability of default and the regulatory "stranding" of assets.

Consistent with the "inventory friction" models of market microstructure (e.g., (Li & Yu 2026)), these results suggest that dealers in the decentralized over-the-counter (OTC) bond market demand a higher liquidity premium to hold the inventory of biodiversity-exposed firms. As biodiversity risk is often opaque and spatially heterogeneous, it increases the search costs for dealers looking to flip these positions, leading to wider bid-ask spreads and higher realized round-trip costs.

Crucially, the sentiment-based measure (*Neg_Score*) provides a definitive resolution to the theoretical ambiguity posed in Section 2.4. The estimate in column (5) corresponds to a 6.2% reduction

[5] We estimate the regressions at the bond-firm-year level.
[6] *Count_Score* (i.e., *exp*(0.040) – 1) and *Reg_Score* (i.e., *exp*(0.046) – 1)

in bond illiquidity.[7] This result provides strong empirical evidence that the *Information Resolution Channel* dominates the *Credit Risk Signaling Channel* in the cross-section. It appears that for complex, high-dimensional risks like biodiversity, market participants penalize "uncertainty" more heavily than they fear "bad news."

By transforming "Knightian uncertainty" into "quantifiable risk," negative disclosures allow dealers to more accurately calibrate credit spreads, thereby reducing the informational frictions that typically plague the secondary bond market. Notably, the magnitude of this liquidity improvement in bonds exceeds the corresponding effect in equities, highlighting that the resolution of uncertainty is a first-order determinant of liquidity for fixed-income instruments.

The control variables behave as expected: larger firms and those with higher analyst coverage exhibit greater liquidity, while longer maturities and lower credit ratings are associated with higher trading costs. To contextualize these effects, prior studies document that biodiversity exposure leads to a 15-percentage-point increase in cash holdings (Ahmad and Karpuz (2024)) and a 93-basis-point increase in credit default spreads (Hoepner *et al.* (2023)). Relative to these benchmarks, the liquidity effects documented here are economically substantial and represent a distinct channel through which biodiversity risk is reflected in firm value.

Overall, our baseline results reveal a nuanced interaction between biodiversity risk exposure and market quality. While the mere presence of nature-related risk exposure imposes a significant 'liquidity tax'—particularly in the decentralized corporate bond market—the strategic use of disclosure tone acts as a powerful mitigant. The fact that negative sentiment improves liquidity in both asset classes confirms that 'uncertainty' is a more potent friction than 'bad news' in the pricing of biodiversity risk. These findings suggest a hierarchy of sensitivity, where fixed-income investors and OTC dealers are more responsive to both the structural threats of biodiversity loss and the informational clarity provided by management. In the following sections, we explore whether these associations are robust

[7] *Neg_Score* (i.e., *exp*(-0.064)-1)

to endogeneity concerns and investigate the specific institutional and attention-based channels that drive this cross-market divergence.

5.2.Robustness tests

This section evaluates the robustness of the baseline association between biodiversity risk exposure and secondary-market liquidity documented in Section 5.1. We assess whether the results are sensitive to alternative liquidity measures, biodiversity exposure proxies, and empirical specifications.

5.2.1. Alternative Liquidity Measures

We first examine whether the baseline findings depend on the specific liquidity proxies used in Table 3. Table 4, Panel A reports results using alternative measures of stock and bond illiquidity.

For equities, we replace the Amihud (2002) illiquidity measure with the cost-per-price proxy of Fong, Holden, and Trzcinka (2017) and the proportion of zero-return trading days of Lesmond, Ogden, and Trzcinka (1999). Across both alternative measures, biodiversity risk exposure measured by the count-based and regulation-based indicators remains positively and significantly associated with stock illiquidity, while the sentiment-based exposure continues to be associated with lower illiquidity. The magnitude and statistical significance of the coefficients are comparable to those reported in Panel A of Table 3.

For corporate bonds, Panel A2 of Table 4 reports results using the Roll (1984)–based effective spread estimator and the intra-quartile price dispersion measure of Han and Zhou (2016). Consistent with the baseline results, bond illiquidity increases with count- and regulation-based biodiversity exposure and decreases when exposure conveys negative sentiment. These findings indicate that the documented liquidity effects are not driven by the choice of a particular liquidity proxy.

[**Insert Table 4 about here**]

5.2.2. First-Difference Specifications

Next, we estimate first-difference regressions that relate changes in liquidity to changes in biodiversity risk exposure, thereby removing all time-invariant firm characteristics without relying on firm fixed effects. Panel B of Table 4 reports these results.

In the bond sample, changes in biodiversity risk exposure $\Delta Biodiversity\ Risk$ are positively and significantly associated with contemporaneous changes in bond illiquidity, while changes in sentiment-based exposure are associated with reductions in illiquidity. These findings reinforce the baseline evidence that biodiversity risk exposure is linked to worsening trading conditions in corporate bond markets.

In contrast, the corresponding coefficients in the stock sample are smaller and statistically insignificant. This difference suggests that liquidity responses to biodiversity risk are more muted in equity markets, potentially reflecting faster information diffusion and greater market depth. The statistically insignificant estimates in the stock sample are likely due to the stock market underpricing biodiversity risk (Huang *et al.* 2024). This is supported by recent studies that document that biodiversity footprint premium began emerging in October 2021 after the Kunming Declaration (see, e.g., Garel *et al.* 2024). The significant coefficient estimates in the bond sample likely reflect the sensitivity of corporate bond liquidity to biodiversity events (see, e.g., Cherief *et al.* 2022).

5.2.3. Alternative Measure of Biodiversity Risk Exposure

To further assess the robustness of our results, we replace the disclosure-based biodiversity exposure measures used in the baseline analysis with a geographic measure of corporate biodiversity exposure (CBE30) developed by Akbari *et al.* (2025).[8] The CBE30 captures firms' exposure to biodiversity-protected areas located within a 30-kilometre radius of their operational sites. Unlike the text-based

[8] We collect establishment-level CBE30 data for firms between 1990 and 2021 from Amir Akbari's research library (https://www.amir-akbari.com/research). In our robustness tests, we aggregate the establishment-level CBE30 for each firm's fiscal year from 2001 to 2021. Therefore, our analysis is at the firm level and not at the establishment level. We standardize CBE30 by taking the natural logarithm of one plus CBE30 and denote it as *logCBE30*.

measures derived from firms' 10-K disclosures, CBE30 reflects firms' physical proximity to biodiversity-sensitive ecosystems and is therefore independent of firms' disclosure or reporting choices.

Panel C of Table 4 reports the results using the alternative measure of biodiversity risk exposure, CBE30, in the natural log form *log(CBE30)*. In the equity sample, the coefficient estimates for *log(CBE30)* are -0.013 and 0.021, and statistically significant in the specifications using *IlliqAM* and *IlliqZeros,* respectively. A 1% increase in the number of protected areas within a 30-km radius of a firm's establishment in the preceding year, $t-1$, is associated with a 0.021% increase in their stock illiquidity (see column (1)). In contrast, the estimate in column (3) suggests that a 1% increase in the number of protected areas within a 30-km radius of a firm's establishment in the preceding level, $t-1$, is associated with a 0.013% decline in the proportion of zero-return trading days.

In the bond sample, the coefficient estimates for *log(CBE30)* range from 0.017 to 0.023 and remain statistically significant across all specifications. These results indicate that greater geographic exposure to biodiversity-protected areas is associated with higher corporate bond trading costs, consistent with the baseline findings based on disclosure-based exposure measures.

Overall, the results using the CBE30 measure provide additional support for the conclusion that biodiversity risk exposure is associated with lower liquidity in secondary markets, particularly in corporate bond markets. Because CBE30 is constructed independently of firms' disclosure behaviour, these findings also mitigate concerns that the baseline results are driven by endogenous reporting incentives.

5.3.Addressing Omitted Variable Bias

We next assess whether the baseline results could be driven by omitted correlated variables using the impact threshold for a confounding variable (ITCV) approach proposed by Frank (2000) and Larcker and Rusticus (2010). The ITCV statistic for biodiversity risk exposure quantifies how strongly an unobserved confounding variable would need to be correlated with both the explanatory variables of

interest and the dependent variables n order to overturn the statistical inference of the baseline estimates. Following prior studies (Larcker & Rusticus 2010; Chen *et al.* 2024), we calculate the ITCV statistic for each of biodiversity risk exposure measure. The statistic is calculated as the product of (i) the partial correlation between biodiversity risk exposure and a given control variable and (ii) the partial correlation between liquidity and that control variable. This procedure allows us to benchmark the potential influence of an omitted confounder relative to the observed covariates in the regression.

[**Insert Table 5 about here**]

The results of this analysis are reported in Table 5. Panel A shows ITCVs of 0.0247 for *Count_Score*, 0.0238 for *Reg_Score* and -0.0220 for *Neg_Score*. Therefore, for all measures of biodiversity risk exposure, overturning the estimated effect would require an omitted confounder with an impact at least as large (in absolute value) as the strongest observed covariates in the regression, namely firm size *log(MCAP)* and the inverse price variable *1/Price*. All other controls are well below these thresholds. Panel B presents the corresponding results for the bond sample. The ITCV values are 0.0057 for *Count_Score*, 0.0071 for *Reg_Score*, and -0.0129 for *Neg_Score*. The largest observed covariates are the coupon rate, bond age, and *log(MCAP)* across all three biodiversity risk exposure measures while the remaining control variables are materially smaller. Overall, these results indicate that an unobserved confounder would need to be at least as influential as the strongest observed covariate to eliminate the estimated biodiversity risk exposure effects. Such a confounder appears unlikely in practice, suggesting that omitted-variable bias is unlikely to fully explain the baseline findings (Larcker & Rusticus 2010; Chen *et al.* 2024). Similar to Ma *et al.* (2025).

5.4.Identification: Evidence from a Quasi-Exogenous Shock

5.4.1. The Deepwater Horizon Oil Spill as an Information Shock

As a further step to address potential endogeneity concerns, we exploit the Deepwater Horizon Oil Spill in 2010 (*hereafter* DWH) as an exogenous shock to firms' environmental risk exposure. The

DWH disaster represented a watershed moment for environmental oversight, triggering unprecedented scrutiny from the U.S. Bureau of Safety and Environmental Enforcement (BSEE) and the introduction of rigorous safety mandates such as the "Well Control Rule." These developments increased pressure on firms, particularly those in environmentally sensitive industries, to disclose environmental risks and improve environmental governance.

Prior research has widely used the DWH disaster as an exogenous shock to examine the effects of environmental risk exposure on corporate outcomes, including firm value (Guo & Zhong 2024), shareholder wealth (Heflin & Wallace 2017), environmental and social performance (Dyck *et al.* 2019), carbon emissions (Safiullah *et al.* 2022) and creditworthiness (Safiullah *et al.* 2021). In our setting, the DWH event provides a plausible shock to the salience of biodiversity-related risks and the information environment surrounding environmentally sensitive firms. While the spill was a fundamental blow to the offending firm, its broader impact was to heighten the "perceived" biodiversity risk across all environmentally sensitive industries due to increased media coverage, litigation risks, and regulatory realignments. Because firms operating in biodiversity-intensive industries are more directly exposed to environmental risks, these firms are expected to experience stronger effects following the spill.

We implement the difference-in-differences (DID) design by partitioning firms into treatment and control groups based on industry-level biodiversity intensity. Following the prior literature (Cherief *et al.* 2022; Becker *et al.* 2025), industries are classified as biodiversity-intensive if their operations have a high dependence on or impact on biodiversity.[9] Firms operating in such industries are therefore more likely to experience heightened biodiversity-related risk exposure following the DWH event. Therefore, we define *Treated* as an indicator variable equal to one for firms operating in biodiversity-intensive industries and zero otherwise. It is important to note that our DID specification

[9] These industries are Agriculture, forestry and fishing, mining, nonmetallic minerals except fuels (quarrying), construction, food and kindred products, textile mill products, paper and allied products, chemicals and allied products, leather and leather products, primary metal industries, and electric, gas and water supply.

relies on industry-level biodiversity intensity rather than firm-level disclosure scores. By defining treatment status based on these structural, pre-determined industry characteristics, we ensure that our liquidity estimates are not biased by the endogenous nature of a firm's choice to disclose specific biodiversity risks in response to the spill. This approach allows us to isolate the market's structural reaction to 'nature-dependency' itself, independent of management's communication strategy.

5.4.2. Diagnostic Tests: Parallel Trends and Pre-Trend Assessment

A critical identifying assumption of the DID framework is that, absent the DWH event, liquidity for treated and control firms would have followed parallel trajectories. We validate this assumption using a dynamic event-study specification, normalizing the interaction between treatment status and event-time indicators relative to the pre-event benchmark ($t = -1$). This specification allows us to evaluate whether treated firms exhibit differential trends prior to the spill and to examine how liquidity evolves following the shock.

Figures 1 and 2 plot the estimated coefficients and corresponding 95% confidence intervals for the interaction terms between treatment status and even-time indicators, normalized relative to the pre-event benchmark period $t = -1$. Three primary insights emerge. First, we find no evidence of differential pre-trends in either the stock or bond illiquidity measures. The estimated coefficients in the pre-treatment periods ($t = -3$ and $t = -2$) are statistically indistinguishable from zero across all liquidity measures. This pattern indicates that treated and control firms follow similar liquidity trajectories prior to the spill, supporting the plausibility of the parallel-trends assumption and strengthening the causal interpretation of the DID estimates.

Second, the post-treatment dynamics differ sharply between equity and bond markets. In the stock sample (Figure 1), the estimated coefficients for post-event periods ($t = 0, 1, 2$) remain close to zero and are not statistically significant across all liquidity measures. These results indicate that the

DWH shock does not generate a statistically significant change in stock market liquidity for firms in biodiversity-intensive industries compared with control firms.

Third, the bond sample exhibits a clear deterioration in liquidity following the DWH event. In Panels A-C of Figure 2, the estimated coefficients become positive and statistically significant starting in the event year ($t = 0$) and remain elevated in subsequent periods ($t = 1$ and $t = 2$). This immediate "step-function" response in the bond market suggests that the shock was rapidly incorporated into dealer pricing and inventory strategies.

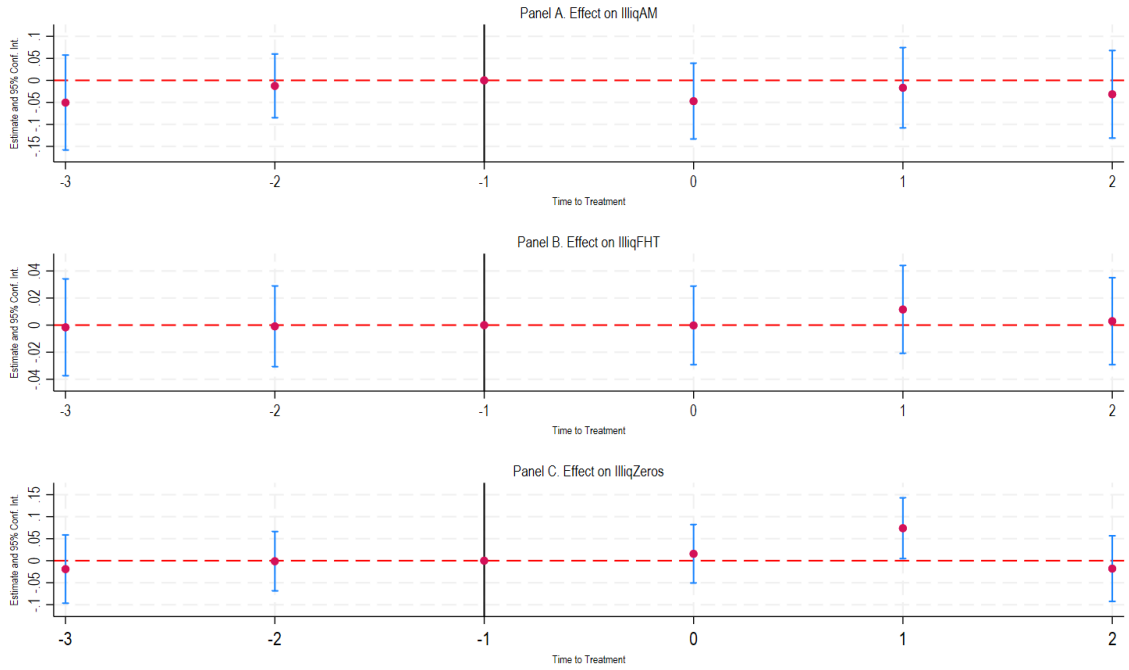


Figure 1. Dynamic treatment effect of the Deepwater Horizon Oil Spill on stock illiquidity. *Notes*. This figure plots the event-study estimates of the effect of the DWH on stock illiquidity. Panels A-C report results for *IlliqAM*, *IlliqFHT*, and *IlliqZeros*. The figure shows coefficient estimates from a dynamic DID specification in which treated firms are interacted with event-time indicators relative to the Oil Spill. The omitted benchmark period is $t = -1$ (the last pre-event period). Dots represent point estimates, and vertical bars denote 95% confidence intervals based on heteroskedasticity-robust, clustered standard errors at the firm level. All regressions include firm- and year-fixed effects.

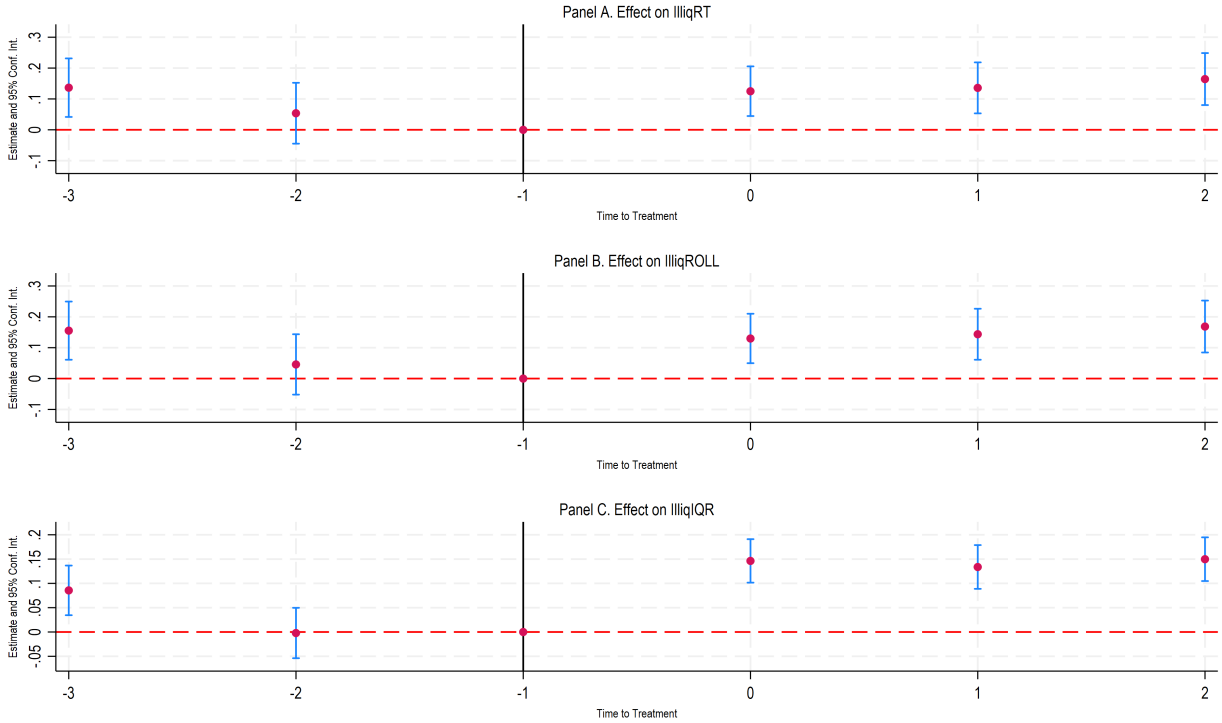


Figure 2. Dynamic treatment effect of the Deepwater Horizon Oil Spill on bond illiquidity. *Notes*. This figure plots the event-study estimates of the effect of the DWH on bond illiquidity. Panels A-C report results for *IlliqRT*, *IlliqROLL*, and *IlliqIQR*. The figure shows coefficient estimates from a dynamic DID specification in which treated firms are interacted with event-time indicators relative to the Oil Spill. The omitted benchmark period is $t = -1$ (the last pre-event period). Dots represent point estimates, and vertical bars denote 95% confidence intervals based on heteroskedasticity-robust, clustered standard errors at the bond level. All regressions include firm- and year-fixed effects.

Overall, the event-study evidence suggests that pre-existing trends are unlikely to drive our findings and reinforces the conclusion that biodiversity-related risk shocks primarily impair liquidity in corporate bond markets while leaving stock market liquidity largely unaffected.

5.4.3. Difference-in-Differences Estimates

We execute our difference-in-differences analysis in two stages. First, we conduct a validation check to confirm that the *Deepwater Horizon* (DWH) event represents a genuine shock to the information environment of biodiversity-intensive firms. Second, we estimate the structural impact of this shock on secondary-market liquidity to identify the causal effect of nature-dependency on trading frictions.

Validation of the Information Shock. Panel A of Table 6 reports the results of regressing our firm-level biodiversity risk exposure metrics on the interaction term *Treated*×*Post,* where *Post* equals one for years after 2010 and zero otherwise. The regression specifications include all firm-level

controls from our baseline model (Equation 1). For the treatment to be valid in our context, we expect a significant increase in biodiversity-related reporting following the spill for firms in nature-intensive industries.

The coefficient estimates on *Treated*×*Post* are positive and statistically significant for both *Count_Score* and *Reg_Score* across the stock and bond samples. This confirms that the DWH event catalyzed a meaningful surge in both biodiversity risk exposure and nature-related regulatory disclosures for firms in biodiversity-intensive industries following the spill. Interestingly, the response of tone related biodiversity risk exposure, *Neg_Score,* exhibits a stark cross-market divergence: the coefficient estimate of *Treated*×*Post* is negative for the stock sample but positive and significant for the bond sample. This suggests that while equity issuers may have strategically moderated their tone to mitigate price volatility or litigation risk (Field *et al.* 2005), the heightened salience of credit risk and the potential for "stranding" compelled firms to provide more candid, negative disclosures to bondholders (Klock *et al.* 2005).

Liquidity Effects. Having validated the shock to the information environment, we examine the impact of the DWH on stocks and bond liquidity using the following DID regression specifications:

$$Stock\ Liquidity_{it} = \alpha + \beta(Treated_i \times Post_t) + \gamma' X_{it} + \delta_i + \theta_t + \varepsilon_{it,} \quad (3)$$

$$Bond\ Liquidity_{jit} = \alpha + \beta(Treated_i \times Post_t) + \partial' W_{it} + \gamma' Z_{jt} + \delta_i + \tau_k + \theta_t + \varepsilon_{jit}, \quad (4)$$

where the dependent variables correspond to the liquidity measures defined in Equations (1) and (2); *Treated* equals one for the firms operating in a biodiversity-intensive industry, and zero otherwise. *Post* equals one for years after 2010 and zero otherwise. δ_i, τ_k, and θ_t denote firm-, industry-, and year-fixed effects, respectively. Bond characteristics and firm-level controls follow the baseline specifications. The variables *Treated* and *Post* are absorbed by the fixed effects and therefore do not appear separately in the regressions. To ensure comparable pre-treatment characteristics between treated and control firms, we apply an entropy balancing technique to construct a matched sample of firms in non-biodiversity-intensive industries (see Hu *et al.* 2025). Therefore, in the regression, each

observation is reweighted using the entropy-balancing weights. $Treated \times Post$ captures differential changes in stock and bond liquidity between firms in biodiversity-intensive industries and those in less biodiversity-intensive industries following the DWH event. If biodiversity risk exposure increases market illiquidity, the coefficient estimates on $Treated \times Post$ would be significantly positive.

[**Insert Table 6 about here**]

Panel B of Table 6 reports the DID estimation results for liquidity. The coefficients reveal a striking asymmetry in how different asset classes absorb systemic biodiversity shocks. In the stock sample (columns 1–3), the estimated coefficients on $Treated \times Post$ economically negligible and statistically insignificant across all three liquidity measures. This indicates that equity market liquidity is relatively resilient to acute biodiversity-related shocks, likely due to the centralized nature of exchange trading and the rapid diffusion of information.

In contrast, the bond sample (columns 4-6) shows a statistically significant and persistent deterioration in liquidity for firms in biodiversity-intensive industries after the spill. The coefficient estimates on *Treated*×*Post* range from 0.048 to 0.074, indicating that bond trading costs on average increase by 4.9% (i.e., *exp*(0.049)-1) to 7.7% (i.e., *exp*(0.074)-1) following the 2010 DWH event. These findings suggest that biodiversity-related shocks primarily impair liquidity in corporate bond markets.

This finding provides a critical refinement to our baseline results and reveals a regime shift in how the market processes nature-related information. While our cross-sectional analysis (Table 3) suggests that a persistent, voluntary negative tone generally facilitates liquidity by resolving valuation uncertainty—consistent with the *Information Resolution Channel*—the DWH results indicate that during an acute systemic crisis, the 'fundamental news' component becomes the dominant driver.

In this high-salience environment, the sudden influx of negative information likely overwhelmed the transparency benefits of the disclosure, fueling concerns over downside credit risk and escalating the inventory-holding costs for bond dealers (Nagel 2012). For bondholders—whose

concave payoff structures make them uniquely sensitive to tail risks—the disclosure of nature-related liabilities was perceived not as a clarifying signal, but as a fundamental threat to solvency. Consequently, the beneficial "uncertainty resolution" of the disclosure was eclipsed by a defensive withdrawal of market participants, leading to the significant deterioration in bond liquidity documented in Panel B.

These DID results provide causal support for our 'participation friction' hypothesis. The significant deterioration in bond liquidity, in contrast to equity market resilience, confirms that biodiversity risk poses a specific structural barrier in dealer-intermediated markets. Crucially, even when transparency increases (as evidenced by the surge in disclosure in Panel A), the fundamental risk shock triggers a defensive withdrawal of liquidity providers in the OTC market. This underscores that 'nature-dependency' acts as a first-order driver of trading frictions that standard, aggregate ESG metrics fail to capture.

Overall, our identification results reveal a stark divergence between equity and bond market resilience. This pattern is consistent with the DWH event primarily escalating credit-market uncertainty and intermediary inventory risk, which disproportionately impairs liquidity in decentralized, OTC bond markets (Hong & Sraer 2013), whereas equity market liquidity is buffered by centralized trading and more efficient information aggregation (Giglio *et al.* 2026).

6. Mechanisms

The empirical evidence in Sections 4 and 5 establishes that biodiversity risk exposure is a significant determinant of market illiquidity, with the effect being particularly acute in corporate bond markets. In this section, we adjudicate between two potential economic mechanisms that may drive this relationship: the *Institutional Participation Channel* and the *Information Production and Attention Channel*. These tests allow us to determine whether the documented illiquidity stems from a contraction in the supply of stable capital or a deterioration of the firm's informational environment.

The first mechanism, corresponding to *Hypothesis 2a*, examines whether biodiversity risk acts as a structural barrier to market entry for sophisticated intermediaries. If nature-related uncertainty leads to a systematic withdrawal of institutional capital, the resulting reduction in participation should mechanically impair market depth and increase transaction costs. The second mechanism, corresponding to *Hypothesis 2b*, investigates whether the high-dimensional complexity of biodiversity risk functions as a "complexity tax" that disincentivizes private information production. By analyzing analyst coverage as a proxy for the equilibrium supply of information, we test whether a retreat in monitoring creates an informational vacuum that exacerbates adverse selection and search costs. Together, these analyses provide a granular view of the structural frictions through which biodiversity-related shocks are priced into market liquidity.

6.1. The Institutional Participation Channel

6.1.1. Biodiversity risk exposure and the Institutional "Exit".

We first examine whether biodiversity risk exposure acts as a participation barrier for sophisticated investors. Following the *Investor Participation Hypothesis* (Hypothesis 2a), if nature-related risks are perceived as unquantifiable or idiosyncratic, institutional investors—who are sensitive to information-processing and monitoring costs (Merton 1987) —may reduce their holdings in biodiversity-intensive firms.

To test this prediction, we analyse the annual change in institutional ownership using data from the 13F institutional holdings database for both the stock and bond samples. We estimate the following empirical model:

$$\Delta Total_IO_{it} = \alpha_0 + \alpha_1 Biodiversity\ Risk\ Exposure_{it} + \gamma' X_{it} + \lambda_i + \delta_k + \theta_t + \varepsilon_{it}, \quad (5)$$

where the dependent variable, $\Delta Total_IO$, represents the annual change in firms' institutional ownership, which is calculated as the institutional ownership in year t minus the institutional ownership in year $t-1$. Biodiversity risk exposure, $Biodiversity\ Risk\ Exposure_{it}$, is measured using the count-based (*Count_Score*), regulatory-based (*Reg_Score*), and sentiment-based

(*Neg_Score*) indicators introduced earlier in the paper. *X* is a vector of control variables: for the stock sample, these include *log(MCAP)*, *CAPXAT*, *ROA*, *RDat* (research and development intensity), and *Adat* (Advertising intensity); for the bond sample, these include offering amount, coupon, bond maturity, bond age, and credit rating. All specifications include firm (λ_i), industry (δ_k), and year (θ_t) fixed effects, with standard errors clustered at the firm level for stocks and at the bond level for bonds.

[**Insert Table 7 about here**]

Panel A of Table 7 reports the results for changes in institutional ownership. In the stock sample, biodiversity risk exposure is associated with a statistically significant decline in institutional ownership. The coefficients on *Count_Score* and *Reg_Score* in columns (1) and (2) are −0.022 (t = −2.74) and −0.022 (t = −2.82), respectively, implying that biodiversity risk exposure is associated with an average of a 2.2 percentage point reduction in institutional holdings. This confirms that institutions "vote with their feet" when faced with high biodiversity exposure. However, we document a striking divergence in how disclosure tone affects this exit, providing evidence for the *Information Resolution Channel* (Hypothesis 3). In the stock sample (Column 3), *Neg_Score* is positively associated with institutional ownership (0.023, t = 2.86). This suggests that in the equity market, explicit transparency regarding adverse risks acts as a *resolution of uncertainty* (Diamond & Verrecchia 1991), providing institutional investors with the "hard information" necessary to maintain their positions.

The bond sample (Columns 4–6) exhibits a more severe pattern of withdrawal. Biodiversity risk exposure is associated with a significant decline in institutional bond ownership across all three measures. The coefficients on *Count_Score*, *Reg_Score*, and *Neg_Score* range from −0.014 to −0.013, indicating that institutional investors reduce their holdings of bonds issued by firms exposed to biodiversity risk. Unlike equity holders, a negative disclosure tone does not mitigate this exit; instead, it is associated with a further reduction in ownership (-0.013, t = -2.87). This suggests that for debt holders, who are primarily concerned with downside credit risk, negative sentiment functions as a

fundamental information shock that triggers an exit, rather than a clarifying disclosure (Klock *et al.* 2005).

Collectively, these results indicate that institutional investors systematically reduce their holdings of firms exposed to biodiversity risk, providing initial evidence consistent with the *Investor Participation Hypothesis* (Hypothesis 2a).

6.1.2. Institutional Exit as a Liquidity Mediation Channel

While the results in Panel A of Table 7 establish that biodiversity risk triggers an institutional exit, we next examine whether this withdrawal is the primary channel driving the liquidity deterioration documented in our baseline analysis. If biodiversity risk impairs liquidity solely by displacing sophisticated participants, the estimated relationship between biodiversity scores and illiquidity should be fully mediated by changes in institutional ownership. To examine this mechanism directly, we re-estimate the baseline liquidity regressions while including both contemporaneous and lagged changes in institutional ownership ($\Delta Total_IO_t$ and $\Delta Total_IO_{t-1}$) as additional controls.

Panel B of Table 7 reports the results of the liquidity regressions after controlling for contemporaneous and lagged institutional flows ($\Delta Total_IO_t$ and $\Delta Total_IO_{t-1}$). In the stock sample (Columns (1) - (3)), the coefficients on *Count_Score* and *Reg_Score* remain positive and statistically significant. This indicates that the institutional exit channel only partially explains the stock liquidity effect, leaving room for other mechanisms, such as the information-processing frictions suggested by the *Investor Attention Channel* (Hypothesis 2b). Interestingly, the coefficient estimate on *Neg_Score* in Column (3) remains negative and highly significant (-0.039, t = -5.94). This confirms that, for stocks, the *Information Resolution Channel* (Hypothesis 3) operates independently of institutional movements: a more transparent, negative-tone biodiversity risk exposure improves liquidity regardless of institutional exit, likely by reducing search costs for the remaining market participants.

The results for the bond sample (Columns 4–6) provide a powerful contrast. In columns (4) and (5), the estimated coefficients on *Count_Score* and *Reg_Score* become statistically insignificant once contemporaneous and lagged changes in institutional ownership are included in the regressions. Simultaneously, the coefficients on institutional ownership changes are positive and highly significant (e.g., Column 5: $\Delta Total_IO_t$ = 0.047, t = 2.63; $\Delta Total_IO_{t-1}$= 0.083, t = 3.25). This finding constitutes a key contribution: it demonstrates that in the over-the-counter (OTC) bond market, the liquidity impact of biodiversity risk is entirely mediated by institutional participation. Because bond liquidity relies on a concentrated group of sophisticated players, their exit creates a structural participation friction. When these key information intermediaries exit—as shown in Panel A—the remaining bond dealers face a more "toxic" or uncertain order flow and must widen bid-ask spreads to protect against inventory risk (Nagel 2012). Furthermore, in Column (6), the coefficient on *Neg_Score* remains statistically significant, indicating that, conditional on the institutional exit, a negative disclosure tone continues to exert a direct influence on bond market liquidity.

Collectively, these findings reinforce the conclusion that biodiversity risk creates a structural participation friction. In the decentralized bond market, where liquidity depends on a small number of sophisticated players, the institutional "exit" triggered by nature-related uncertainty is the primary mechanism through which biodiversity risk impairs market quality.

6.2.The Information Production and Attention Channel

6.2.1. Biodiversity risk exposure and the Supply of Information

We next investigate whether biodiversity risk exposure functions as an informational friction that disincentivizes private information production. Following the *Investor Attention Hypothesis* (Hypothesis 2b), nature-related risks represent a form of high-dimensional, non-standard information that requires specialized expertise to decode (Peng & Xiong 2006). We utilize analyst coverage as a proxy for the equilibrium level of private information production. In a competitive market for

information, the decision to maintain coverage reflects an optimization problem where the marginal cost of processing complex signals is weighed against the expected value of the coverage. If the costs of processing biodiversity-related disclosures exceed the marginal benefit of coverage, we should observe a systematic reduction in the informational environment, proxied by analyst coverage.

To examine this mechanism, we analyze whether biodiversity risk exposure predicts a shift toward a more sparse informational environment, proxied by a decline in analyst coverage. Following prior literature, we define limited investor attention as a binary state where a firm's coverage falls below the sample median. Firms with fewer analysts generally experience weaker information production and higher search costs for investors.[10] Specifically, we estimate the following regression to capture the dynamics of this information attrition:

$$\Delta Low_Coverage_{it} = \alpha_0 + \alpha_1 Biodiversity\ Risk\ Exposure_{it} + \gamma' X_{it} + \lambda_i + \delta_k + \theta_t + \varepsilon_{it}, (6)$$

where the dependent variable, $\Delta Low_Coverage$, measures the change in the low analyst coverage indicator between year $t-1$and year t, which is defined as the low analyst coverage in year t minus the low analyst coverage in year $t-1$. The key independent variable, $Biodiversity\ Risk\ Exposure$ is measured using the count-based (*Count_Score*), regulatory-based (*Reg_Score*), and sentiment-based (*Neg_Score*) indicators introduced earlier in the paper. The control variables and fixed effects follow the baseline specifications in Equations (1) and (2), and standard errors are clustered at the firm level for stocks and at the bond level for bonds.

[**Insert Table 8 about here**]

Panel A of Table 8 presents the results of our analysis on information attrition. We document a sharp structural divergence in how biodiversity risk exposure shapes the informational environment across asset classes. In the stock sample, the coefficients on *Count_Score* and *Reg_Score* in columns (1) and (2) are positive but statistically insignificant, suggesting that the equity market's information

[10] We justify the use of fewer analysts covering the firm as a proxy for investor limited attention on the basis that, in a survey of sell-side analysts, Brown *et al.* (2015) find that client (i.e., institutional investors) demand primarily motivates analysts to provide accurate earnings forecasts and profitable recommendations.

production is resilient to nature-related complexity. This is consistent with the notion that the non-linear upside of equity provides sufficient incentives for analysts to bear the high costs of processing specialized biodiversity signals.

In contrast, the bond sample (Columns 4–5) reveals a systematic retreat in coverage. The coefficients on *Count_Score* (0.075, t = 7.46) and *Reg_Score* (0.044, t = 4.99) are positive and highly significant at the 1% level, indicating that biodiversity risk exposure is a potent driver of information attrition in debt markets. This suggests a structural divergence between asset classes: while equity analysts—incentivized by the non-linear upside of firm value—maintain coverage, bond analysts face an "asymmetric complexity tax". Given that bondholders are primarily concerned with downside solvency, the high cost of auditing biodiversity-related "tail risks" disincentivizes analyst monitoring, leading to a thinner informational environment.

Interestingly, the sentiment-based measure *Neg_Score* coefficient estimates (Columns 3 and 6) are negative and statistically significant (−0.036, t = −3.66 for stocks; (−0.075, t = −5.37 for bonds). This suggests that while raw exposure creates complexity, explicitly negative biodiversity exposure serves as a clarifying signal. By providing "hard information" regarding a firm's potential liabilities, such disclosures lower the marginal cost of information acquisition, effectively "attracting" analyst scrutiny and mitigating the attention constraints otherwise associated with biodiversity-intensive firms.

6.2.2. Information Attrition as a Liquidity Mediation Channel

We next examine whether this "information desert" serves as the causal conduit for the illiquidity documented in our baseline results. If biodiversity risk impairs market quality by increasing search costs and adverse selection through a lack of monitoring, the inclusion of analyst coverage should mediate the baseline relationship.

To test this mechanism, we re-estimate the baseline liquidity regressions while controlling for contemporaneous and lagged changes in the information environment ($\Delta Low_Coverage_t$ and $\Delta Low_Coverage_{t-1}$) as additional controls. Panel B of Table 8 reports the estimation results.

In the stock sample, the coefficients on *Count_Score* and *Reg_Score* remain positive and statistically significant in columns (1) and (2), while *Neg_Score* remains negatively associated with *IlliqAM* in column (3). These findings suggest that in the centralized equity market, the liquidity impact of biodiversity risk is not a mere byproduct of analyst coverage, but likely reflects broader fundamental uncertainty or heterogeneous beliefs among market participants.

The bond sample, however, provides striking evidence of full mediation. As showed in columns (4)–(6), the coefficients on *Count_Score, Reg_Score*, and *Neg_Score* become statistically insignificant once contemporaneous and lagged changes in analyst coverage are included. At the same time, the coefficient on the lagged change in low analyst coverage ($\Delta Low_Coverage_{t-1}$) is positive and statistically significant across all specifications, indicating that a prior contraction in the supply of information precedes the deterioration of bond liquidity. This lead-lag relationship suggests that in the decentralized OTC market, the retreat of information intermediaries creates an **informational vacuum**. Unlike the institutional exit in Section 6.1, which represents a withdrawal of trading capital, the analyst exit represents a breakdown in the price discovery process. Without the "anchor" of analyst research, dealers face heightened adverse selection risk and higher search costs. To protect against trading with better-informed counterparties in an opaque environment, dealers must widen bid-ask spreads. Notably, the estimated coefficient on *Neg_Score* also becomes insignificant (-0.037; t = -1.54), indicating that the liquidity-enhancing effect of tone disclosure is entirely filtered through its ability to maintain the information environment. Collectively, these results provide robust support for *Hypothesis 2b*, identifying the *Information Production Channel* as a dominant structural driver of illiquidity in corporate bond markets.

7. Conclusion

This paper provides the first comprehensive analysis of how firm-level biodiversity risk exposure shapes secondary-market liquidity across equity and corporate bond markets. By integrating multidimensional text-based exposure metrics with trading data, we move beyond the study of asset price levels to document the fundamental trading frictions associated with nature-related complexity. Our analysis identifies a significant "liquidity tax" imposed by ecological risks and uncovers the structural mechanisms that transmit these risks through the financial system.

Our results establish that biodiversity risk is a first-order determinant of market illiquidity, characterized by a sharp structural divergence between asset classes. While the impact on equity markets is statistically detectable, the deterioration in market quality is substantially more acute and persistent in the corporate bond market. We show that this asymmetry is not a mere byproduct of firm fundamentals, but is instead driven by the search-intensive, dealer-intermediated architecture of the over-the-counter (OTC) bond market. In this decentralized environment, the high-dimensional complexity inherent in biodiversity signals triggers a defensive withdrawal of liquidity provision—a friction that is largely buffered in the more diverse and centralized equity market. These effects are economically meaningful and robust across alternative liquidity measures, alternative biodiversity exposure proxies, and a range of identification strategies designed to mitigate endogeneity concerns.

By adjudicating between competing economic channels, we identify the *Institutional Participation Channel* and the *Information Production and Attention Channel* as the primary conduits of this illiquidity. In the bond market, the relationship between biodiversity exposure and trading costs is entirely mediated by a systematic "institutional exit" and a contraction in analyst monitoring. This dual attrition of trading capital and private information production creates an "informational vacuum," forcing dealers to widen bid-ask spreads to protect against heightened inventory and adverse selection risks. These results confirm that biodiversity risk functions as a first-order participation friction, where the specialized expertise required to decode nature-dependency discourages the very intermediaries essential for market depth.

Conversely, the equity market exhibits a significant degree of resilience. While biodiversity risk triggers a similar reduction in institutional ownership and analyst attention, these channels provide only partial mediation for stock illiquidity. This suggests that the centralized architecture of equity exchanges, characterized by a more heterogeneous participant base and lower search frictions, provides a "liquidity floor" that buffers the market against the retreat of sophisticated intermediaries. Thus, while the "complexity tax" of biodiversity risk is universal, its ability to impair market quality is endogenously determined by the structural reliance of the asset class on concentrated institutional intermediation

A key contribution of our study is the documentation of the state-dependency of nature-related disclosures. In a steady-state equilibrium, we find that a negative biodiversity-related disclosure tone actually facilitates liquidity by resolving valuation uncertainty—demonstrating that for complex environmental risks, the resolution of "Knightian uncertainty" through transparent communication is a first-order lubricant for market quality. However, using the 2010 *Deepwater Horizon* oil spill as a quasi-exogenous shock, we demonstrate that this relationship shifts fundamentally during acute crises. When biodiversity risk becomes hyper-salient, the *Credit Risk Signaling Channel* overrides the benefits of transparency. In this high-salience regime, bond dealers treat exposed assets as "toxic inventory," leading to a systemic collapse in liquidity.

As global initiatives such as the Taskforce on Nature-related Financial Disclosures (TNFD) move toward standardized reporting, our findings have significant implications for both policymakers and market participants. For investors, we show that biodiversity exposure creates a "liquidity premium" that must be managed alongside fundamental solvency risk. For firms, our evidence suggests that while transparent, high-quality communication can mitigate trading frictions in normal times, it may not shield debt instruments from liquidity shocks during environmental disasters. Ultimately, as ecological thresholds are increasingly tested, understanding the intersection of biodiversity risk and market microstructure will be essential for ensuring the resilience of the global financial architecture.

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Table 1. Descriptive Statistics

The table reports sample means, medians, standard deviations (SD), and interquartile ranges (P25–P75) for equities (Panel A, firm–year) and corporate bonds (Panel B, bond–year). *IlliqAM* is the Amihud (2002) illiquidity measure. *IlliqFHT* and *IlliqZeros* are the alternative stock illiquidity measures developed by Fong et al. (2017) and Lesmond et al (1999). *Count_Score*, *Reg_Score*, and *Neg_Score* are indicator variables equal to 1 when the firm exhibits a biodiversity-exposure signal based on the count-based metric, regulation-based metric, or negative-tone metric, respectively, and 0 otherwise. *log*(MCAP) is the natural log of market capitalization. *log(MB)* is the natural log of the book-to-market ratio. *log*(Std_Ret) is the natural log of monthly stock-return volatility computed over the prior 12 months. *ln_Analysts* is log(1 + number of analysts). *Total_IO* is institutional ownership (fraction of shares held by institutions). *1/Price* is the inverse of the year-end stock price. *CAPXAT* is capital expenditures scaled by total assets. *ROA* is return on assets (net income divided by total assets). *IlliqRT* is the dollar-weighted round-trip trading cost following Feldhütter (2012). *IlliqROLL* and *IlliqIQR* are the alternative bond illiquidity measures following Dick-Nielsen et al. (2012) and Schestag et al. (2016). *Offering_amount* is the new-issue size. *Coupon rate* is the annual coupon percentage. *Bond_maturity* is years to maturity; *Bond_age* is years since issuance. *Credit rating* is a numeric rating scale (higher values denote higher credit quality).

Panel A. Stock sample

	Obs	Mean	Median	SD	P25	P75
IlliqAM	35,787	0.186	0.004	0.602	0.001	0.046
IlliqFHT	35,787	0.184	0.080	0.255	0.028	0.239
IlliqZeros	35,787	0.956	0.786	0.712	0.335	1.429
Count_Score	35,787	0.423	0.000	0.494	0.000	1.000
Reg_Score	35,787	0.416	0.000	0.493	0.000	1.000
Neg_Score	35,787	0.589	1.000	0.492	0.000	1.000
log(MCAP)	35,787	13.633	13.607	2.148	12.119	15.066
log(Std_Ret)	35,787	-3.575	-3.602	0.529	-3.961	-3.210
ROA	35,787	0.025	0.087	0.250	0.019	0.135
CAPXAT	35,787	0.043	0.024	0.106	0.011	0.050
log(MB)	35,787	1.319	1.176	0.700	0.845	1.618
ln_Analysts	35,787	2.606	3.258	2.168	0.000	4.543
Total_IO	35,787	0.380	0.249	0.465	0.000	0.571
1/Price	35,787	0.142	0.044	0.274	0.021	0.123

Panel B. Bond sample

	Obs	Mean	Median	SD	P25	P75
IlliqRT	67,414	1.634	1.615	0.758	1.068	2.140
IlliqROLL	67,105	0.781	0.667	0.684	0.153	1.252
IlliqIQR	67,414	0.771	0.696	0.494	0.390	1.056
Count_Score	67,414	0.388	0.000	0.487	0.000	1.000
Reg_Score	67,414	0.372	0.000	0.483	0.000	1.000
Neg_Score	67,414	0.664	1.000	0.472	0.000	1.000
Offering amount	67,414	0.637	0.500	0.505	0.300	0.750
Coupon rate	67,414	5.157	5.125	1.993	3.700	6.400
Bond maturity	67,414	13.783	10.000	9.561	7.000	20.000
Bond age	67,414	4.019	3.000	3.577	1.000	6.000
Credit rating	67,414	15.679	17.000	5.368	14.000	19.000
log(MCAP)	41,258	10.317	10.383	1.577	9.347	11.455
ROA	43,657	0.112	0.104	0.081	0.076	0.143

Table 2 . 10-K biodiversity scores by industry.

Industry	Count_Score	Reg_Score	Neg_Score
Agriculture, forestry, and fishing	1.000	1.000	0.000
Mining	0.485	0.485	0.579
Nonmetalic Minerals Except Fuels	0.291	0.279	0.741
Construction	0.372	0.372	0.626
Food and Kindred Products	0.326	0.326	0.687
Tobacco Products	0.228	0.228	0.758
Textile Mill Products	0.326	0.326	0.685
Paper and Allied Products	0.401	0.369	0.638
Printing and Publishing	0.534	0.436	0.598
Chemicals and Allied Products	0.447	0.439	0.542
Petroleum and Coal Products	0.511	0.500	0.534
Rubber and Miscellaneous Plastics Products	0.676	0.676	0.324
Leather and Leather Products	0.138	0.138	0.862
Primary Metal Industries	0.381	0.358	0.642
Fabricated Metal Products	0.196	0.174	0.843
Machinery, Except Electrical	0.191	0.191	0.809
Electrical and Electronic Equipment	0.263	0.263	0.737
Transportation Equipment	0.351	0.351	0.649
Instruments and Related Products	0.270	0.267	0.732
Miscellaneous Manufacturing Industries	0.402	0.402	0.598
Transportation	0.226	0.185	0.817
Telephone and Telegraph Communication	0.372	0.372	0.628
Electric, Gas, and Water Supply	0.477	0.433	0.702
Wholesale	0.319	0.319	0.681
Retail Stores	0.374	0.364	0.637
Services	0.364	0.363	0.637
Public Administration	0.598	0.598	0.402

Notes. This table reports the biodiversity score distribution by industry, where industries are defined based on the Fama-French 38 industry classification.

Table 3. Biodiversity risk exposure and liquidity in the stock and corporate bond market.

Panel A. Stock Sample

	Dependent variable: $IlliqAM$					
	Count_Score		*Reg_Score*		*Neg_Score*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Risk Exposure	0.261***	0.129***	0.266***	0.129***	-0.048***	-0.037***
	(10.31)	(6.51)	(10.28)	(6.36)	(-7.88)	(-6.02)
$log(MCAP)_{t-1}$		-0.154***		-0.156***		-0.016***
		(-9.20)		(-9.19)		(-6.58)
$log(MB)_{t-1}$		-0.070***		-0.071***		-0.007***
		(-5.17)		(-5.17)		(-3.62)
$log(Std_Ret)_{t-1}$		-0.032		-0.031		-0.018***
		(-0.97)		(-0.94)		(-4.40)
$Ln_Analyst_{t-1}$		-0.031**		-0.032**		-0.003*
		(-2.05)		(-2.07)		(-1.85)
$Total_IO_{t-1}$		-0.098		-0.100		0.012
		(-1.50)		(-1.53)		(1.57)
$1/Price_{t-1}$		0.268***		0.266***		0.194***
		(5.37)		(5.30)		(5.78)
$CAPXAT$		-0.443***		-0.441***		-0.031*
		(-4.24)		(-4.14)		(-1.75)
ROA		-0.204***		-0.207***		-0.034***
		(-6.20)		(-6.26)		(-3.45)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,787	34,739	35,787	34,739	35,787	34,739
Adjusted R^2	0.763	0.795	0.765	0.797	0.385	0.394

Panel B. Bond Sample

	Dependent variable: *IlliqRT*					
	Count_Score		*Reg_Score*		*Neg_Score*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Risk Exposure	0.021*	0.040***	0.027**	0.046***	-0.064***	-0.064***
	(1.92)	(2.92)	(2.43)	(3.15)	(-4.60)	(-4.13)
Offering Amount		0.002		0.004		0.003
		(0.29)		(0.47)		(0.44)
Coupon		0.030***		0.030***		0.039***
		(11.01)		(11.04)		(16.92)
Bond Maturity		0.143***		0.144***		0.146***
		(59.69)		(59.42)		(80.02)
Bond Maturity Squared		-0.003***		-0.003***		-0.003***
		(-41.62)		(-41.64)		(-55.64)
Bond Age		-0.061***		-0.062***		-0.060***
		(-55.39)		(-55.64)		(-63.68)
Credit Rating		0.018***		0.017***		0.019***
		(21.15)		(20.30)		(25.77)
$log(MCAP)_{t-1}$		-0.094***		-0.093***		-0.073***
		(-7.95)		(-7.84)		(-7.25)
ROA_{t-1}		-0.430***		-0.441***		-0.402***
		(-6.77)		(-6.93)		(-7.06)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,414	29,157	67,414	29,157	67,414	29,157
Adjusted R^2	0.325	0.697	0.326	0.695	0.296	0.748

Notes. This table reports the estimates of OLS regressions of stock market liquidity and corporate bond liquidity on firms' biodiversity risk exposure and control variables. All regressions include year, firm and industry fixed effects. Industry fixed effects are based on the Fama and French 38 industry classification. Standard errors are clustered at the firm level for equities and at the bond level for bonds. Robust standard errors are in parentheses. Detailed variable definitions are provided in the Appendix. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

Table 4. Robustness tests.

Panel A. Alternative measures of liquidity.

Panel A1. Stock Sample

	Count Score		*Reg Score*		*Neg Score*	
Dependent Variables	*IlliqFHT*	*IlliqZeros*	*IlliqFHT*	*IlliqZeros*	*IlliqFHT*	*IlliqZeros*
Biodiversity Risk	0.091***	0.259***	0.092***	0.264***	-0.023***	-0.104***
	(11.09)	(13.24)	(10.92)	(13.18)	(-6.46)	(-6.41)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,251	34,251	34,251	34,251	34,251	34,251
Adjusted R^2	0.753	0.741	0.753	0.742	0.540	0.504

Panel A2. Bond Sample

	Count Score		*Reg Score*		*Neg Score*	
Dependent Variables	*IlliqROLL*	*IlliqIQR*	*IlliqROLL*	*IlliqIQR*	*IlliqROLL*	*IlliqIQR*
Biodiversity Risk	0.036**	0.027*	0.027*	-0.038*	-0.038*	-0.044***
	(2.25)	(1.65)	(1.65)	(-1.89)	(-1.89)	(-4.29)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Bond controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,012	29,157	30,012	29,157	30,012	29,157
Adjusted R^2	0.367	0.685	0.366	0.683	0.422	0.734

Panel B. First difference of dependent variables

	Stock Sample			Bond Sample		
Dep. var:	$\Delta IlliqAM$			$\Delta IlliqRT$		
	Count_ Score	*Reg_ Score*	*Neg_ Score*	*Count_ Score*	*Reg_ Score*	*Neg_ Score*
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Biodiversity\ Risk$	0.151	0.152	-0.156	0.072***	0.086***	-0.189***
	(1.40)	(1.39)	(-1.39)	(3.39)	(3.46)	(-7.79)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock controls	Yes	Yes	Yes	No	No	No
Bond controls	No	No	No	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	No	No	No
Observations	32,022	32,022	32,022	31,797	31,797	31,797
Adjusted R^2	0.189	0.189	0.189	0.056	0.056	0.055

Panel C. Alternative Measure of Corporate Biodiversity Risk Exposure using Akbari et al. (2025) CBE30

	Stock Sample			Bond Sample		
Dep. var:	*IlliqAM*	*IlliqFHT*	*IlliqZeros*	*IlliqRT*	*IlliqROLL*	*IlliqIQR*
	(1)	(2)	(3)	(4)	(5)	(6)
$log(CBE30)_{t-1}$	0.021***	0.003	-0.013**	0.023***	0.018**	0.017***
	(5.34)	(1.60)	(-2.49)	(3.83)	(2.12)	(4.32)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock controls	Yes	Yes	Yes	No	No	No
Bond controls	No	No	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,499	20,499	20,499	15,871	16,389	15,871
Adjusted R^2	0.568	0.635	0.678	0.750	0.397	0.736

Notes. Control variables in Panel A include firm size (*log(MCAP)*), R&D expenditures (*RDat*), advertising expenses (*ADat*), book leverage (*bklev*), firm age (*logage*), institutional ownership (*Total_IO*), analyst coverage (*ln_analysts*), stock price level (*inv_price*), and return volatility (*std_ret*), all lagged one year. Control variables in Panel B include bond characteristics (offering amount, coupon, bond maturity, bond maturity squared, bond age, and credit rating) and firm-level factors (Tobin Q, book leverage, and asset tangibility). All specifications include firm fixed effects, year fixed effects, and either industry × year fixed effects (Panel A) or industry time trends (Panel B). Robust *t*-statistics, clustered at the firm level and bond level, respectively, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Table 5. Impact Threshold for a confounding variable (ITCV) test statistic.

This table reports the estimates of OLS regressions of stock market illiquidity on the biodiversity score and control variables. All regressions include both firm and industry-year fixed effects. Industry fixed effects are based on the Fama and French 38 industry classification. Standard errors are clustered at the firm level in Panel A and bond level in Panel B. Detailed variable definitions are provided in the Appendix. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Stock Sample						
	Dependent variable: $IlliqAM$					
	Count_Score		*Reg_Score*		*Neg_Score*	
	ITCV	Impact (Partial)	ITCV	Impact (Partial)	ITCV	Impact (Partial)
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Risk	0.0247		0.0238		-0.0220	
log(MCAP)		0.0400		0.0413		-0.0441
log(MB)		0.0032		0.0029		-0.0024
log(Std_Ret)		0.0002		0.0002		-0.0001
ln_Analysts		0.0077		0.0078		-0.0079
Total IO		0.0024		0.0026		-0.0025
1/Price		0.0254		0.0258		-0.0253
CAPXAT		0.0000		0.0001		-0.0002
ROA		-0.0092		-0.0092		0.0090
Panel B. Bond Sample						
	Dependent variable: *IlliqRT*					
	Count_Score		*Reg_Score*		*Neg_Score*	
	ITCV	Impact (Partial)	ITCV	Impact (Partial)	ITCV	Impact (Partial)
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Risk	0.0057		0.0071		-0.0129	
Offering amount		-0.0014		-0.0012		0.0010
Coupon rate		0.0135		0.0139		-0.0171
Bond maturity		0.0019		0.0008		-0.0039
Bond maturity Squared		0.0014		0.0008		-0.0037
Bond age		0.0158		0.0152		-0.0199
Credit rating		-0.0009		-0.0008		0.0018
log(MCAP)		0.0116		0.0112		-0.0096
ROA		0.0050		0.0048		-0.0026

Table 6. Difference-in-Differences Analysis Using the 2010 Deepwater Horizon Oil Spill.

Panel A. Effect of the 2010 Deepwater Horizon Oil Spill on Biodiversity Risk Exposure

	Stock Sample		
	Count_Score	*Reg_Score*	*Neg_Score*
Variables	(1)	(2)	(3)
Treated × *Post*	0.048***	0.043***	-0.036**
	(3.05)	(2.84)	(-2.41)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	34,789	34,789	34,789
Adjusted R^2	0.753	0.763	0.782
	Bond Sample		
	Count_Score	*Reg_Score*	*Neg_Score*
Variables	(1)	(2)	(3)
Treated × *Post*	0.041***	0.044***	0.028***
	(4.54)	(4.95)	(3.06)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	41,114	41,114	41,114
Adjusted R^2	0.711	0.733	0.790

Panel B. DID Estimation

	Stock Sample			**Bond Sample**		
Dep. var:	*IlliqAM*	*IlliqFHT*	*IlliqZeros*	*IlliqRT*	*IlliqROLL*	*IlliqIQR*
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × *Post*	-0.003	-0.005	-0.017	0.050**	0.074**	0.048***
	(-0.17)	(-0.78)	(-0.92)	(1.98)	(2.55)	(3.01)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Bond controls	No	No	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond × Firm FE	No	No	No	Yes	Yes	Yes
Observations	33,687	33,687	33,687	30,820	31,893	30,820
Adjusted R^2	0.487	0.633	0.608	0.714	0.356	0.685

Notes. Control variables in Panel A include firm size (*log(MCAP)*), R&D expenditures (*RDat*), advertising expenses (*ADat*), book leverage (*bklev*), firm age (*logage*), institutional ownership (*Total_IO*), analyst coverage (*ln_analysts*), stock price level (*inv_price*), and return volatility (*std_ret*), all lagged one year. Control variables in Panel B include bond characteristics (offering amount, coupon, bond maturity, bond maturity squared, bond age, and credit rating) and firm-level factors (Tobin Q, book leverage, and asset tangibility). All specifications include firm fixed effects, year fixed effects, and either industry × year fixed effects (Panel A) or industry time trends (Panel B). Robust *t*-statistics, clustered at the firm level and bond level, respectively, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Table 7. Biodiversity Risk Exposure, Institutional Ownership, and Liquidity of Stock and Bonds

Panel A. Biodiversity Risk Exposure and Changes in Institutional Ownership

	Stock Sample			Bond Sample		
Dep. var:	$\Delta Institutional\ Ownership$			$\Delta Institutional\ Ownership$		
	Count_ Score	*Reg_ Score*	*Neg_ Score*	*Count_ Score*	*Reg_ Score*	*Neg_ Score*
	(1)	(2)	(3)	(4)	(5)	(6)
$Biodiversity\ Risk$	-0.022***	-0.022***	0.023***	-0.014***	-0.015**	-0.013***
	(-2.74)	(-2.82)	(2.86)	(-2.64)	(-2.52)	(-2.87)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	No	No	No
Observations	35,209	35,209	35,209	24,566	24,566	24,566
Adjusted R^2	0.343	0.343	0.343	0.029	0.030	0.027

Panel B. Biodiversity Risk Exposure, Changes in Institutional Ownership and Liquidity of Stocks and Bonds

	Stock Sample			Bond Sample		
Dep. var:	*IlliqAM*			*IlliqRT*		
	Count_ Score	*Reg_ Score*	*Neg_ Score*	*Count_ Score*	*Reg_ Score*	*Neg_ Score*
	(1)	(2)	(3)	(4)	(5)	(6)
$Biodiversity\ Risk$	0.115***	0.116***	-0.039***	0.029	0.026	-0.041*
	(5.60)	(5.47)	(-5.94)	(1.54)	(1.30)	(-1.67)
$\Delta Total_IO$	0.081**	0.083**	0.022***	0.046**	0.047***	0.028**
	(2.11)	(2.13)	(3.37)	(2.57)	(2.63)	(2.10)
$\Delta Total_IO_{t-1}$	-0.042	-0.043	0.017***	0.082***	0.083***	0.052***
	(-1.18)	(-1.19)	(3.02)	(3.25)	(3.25)	(2.77)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,301	31,301	31,301	17,130	17,130	17,130
Adjusted R^2	0.812	0.814	0.391	0.725	0.723	0.762

Notes. Control variables in Panel A include firm size (*log(MCAP)*), R&D expenditures (*RDat*), advertising expenses (*ADat*), book leverage (*bklev*), firm age (*logage*), institutional ownership (*Total_IO*), analyst coverage (*ln_analysts*), stock price level (*inv_price*), and return volatility (*std_ret*), all lagged one year. Control variables in Panel B include bond characteristics (offering amount, coupon, bond maturity, bond maturity squared, bond age, and credit rating) and firm-level factors (Tobin Q, book leverage, and asset tangibility). All specifications include firm fixed effects, year fixed effects, and either industry × year fixed effects (Panel A) or industry time trends (Panel B). Robust *t*-statistics, clustered at the firm level and bond level, respectively, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Table 8. Biodiversity Risk Exposure, Analyst Coverage, and Liquidity of Stock and Bonds

Panel A. Biodiversity Risk Exposure and Changes in Analyst Coverage

	Stock Sample			Bond Sample		
Dep. var:	$\Delta Low\ Coverage$			$\Delta Low\ Coverage$		
	Count_ Score	*Reg_ Score*	*Neg_ Score*	*Count_ Score*	*Reg_ Score*	*Neg_ Score*
	(1)	(2)	(3)	(4)	(5)	(6)
$Biodiversity\ Risk$	0.015	0.013	-0.036***	0.075***	0.044***	-0.075***
	(1.13)	(0.94)	(-3.66)	(7.46)	(4.99)	(-5.37)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	No	No	No
Observations	34,732	34,732	34,732	24,566	24,566	24,566
Adjusted R^2	0.059	0.061	0.006	0.070	0.068	0.065

Panel B. Biodiversity Risk Exposure, Changes in Analyst Coverage and Liquidity of Stocks and Bonds

	Stock Sample			Bond Sample		
Dep. var:	*IlliqAM*			*IlliqRT*		
	Count_ Score	*Reg_ Score*	*Neg_ Score*	*Count_ Score*	*Reg_ Score*	*Neg_ Score*
	(1)	(2)	(3)	(4)	(5)	(6)
$Biodiversity\ Risk$	0.114***	0.115***	-0.039***	0.023	0.016	-0.037
	(5.54)	(5.41)	(-5.83)	(1.23)	(0.80)	(-1.54)
$\Delta Low\ Coverage$	0.019	0.019	0.006*	0.013	0.019*	0.005
	(1.26)	(1.26)	(1.72)	(1.16)	(1.72)	(0.49)
$\Delta Low\ Coverage_{t-1}$	-0.022	-0.023	0.004*	0.027**	0.030***	0.023**
	(-1.08)	(-1.08)	(1.73)	(2.46)	(2.73)	(2.49)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,301	31,301	31,301	17,130	17,130	17,130
Adjusted R^2	0.811	0.813	0.390	0.724	0.724	0.761

Notes. Control variables in Panel A include firm size (*log(MCAP)*), R&D expenditures (*RDat*), advertising expenses (*ADat*), book leverage (*bklev*), firm age (*logage*), institutional ownership (*Total_IO*), analyst coverage (*ln_analysts*), stock price level (*inv_price*), and return volatility (*std_ret*), all lagged one year. Control variables in Panel B include bond characteristics (offering amount, coupon, bond maturity, bond maturity squared, bond age, and credit rating) and firm-level factors (Tobin Q, book leverage, and asset tangibility). All specifications include firm fixed effects, year fixed effects, and either industry × year fixed effects (Panel A) or industry time trends (Panel B). Robust *t*-statistics, clustered at the firm level and bond level, respectively, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix. Variable Definitions

Variables	Acronym	Description	Data sources
A. Liquidity measures			
(i). Stock liquidity measures			
Amihud illiquidity	*IlliqAM*	Log of one plus the average daily Amihud (2002) illiquidity ratio for firm *i* in fiscal year *t*, in which the daily Amihud ratio is calculated as the absolute value of stock return divided by dollar trading volume on a given day. Daily dollar volume for NASDAQ stocks is halved to adjust for double-counting. The ratio is scaled by 1,000,000 following the standard convention.	CRSP
Cost-per-price illiquidity	*IlliqFHT*	The Fong, Holden, and Trzcinka (2017) illiquidity measure, calculated as FHT = 2 $\times \sigma \times \Phi^{-1}$((1 + zeros) / 2), where σ is the standard deviation of non-zero daily returns and $zeros$ is the proportion of zero-return days. The raw FHT value is multiplied by 100 for readability, and the final measure is constructed as *IlliqFHT* = ln(FHT + 1). The log transformation reduces skewness and compresses extreme values while preserving the ordering of illiquidity across firms. Higher values indicate greater illiquidity.	CRSP
Zero-return illiquidity	*IlliqZeros*	The number of trading days with zero returns divided by the total number of trading days with valid returns, following Lesmond, Ogden, and Trzcinka (1999). The raw proportion is then multiplied by 100 for readability, and the final measure *IlliqZeros*, is constructed as the natural logarithm of one plus the scaled proportion. A higher proportion of zero-return days indicates lower liquidity and higher transaction costs.	CRSP
(ii). Bond liquidity measures			
Round-trip transaction cost	*IlliqRT*	Log of one plus the round-trip transaction cost estimator proposed by Feldhütter (2012). For each bond, the round-trip cost is calculated as twice the difference between the lowest and highest transaction prices observed within a trading round	WRDS Bond Returns

		trip during the quarter, scaled by the average of the maximum and minimum transaction prices. Quarterly estimates are averaged within each fiscal year. Higher values indicate larger trading costs and lower bond market liquidity.	
Roll spread	*IlliqROLL*	Log of one plus the modified intra-month Roll (1984) estimator for effective bid-ask spreads, following Dick-Nielsen, Feldhütter, and Lando (2012). The Roll estimator captures effective spreads through the negative autocovariance of transaction prices induced by bid-ask bounce, computed from end-of-month bond returns. Monthly estimates are aggregated at the bond level by taking the annual median.	WRDS Bond Returns
Interquartile price range	*IlliqIQR*	Log of one plus the interquartile price range measure introduced by Schestag, Schuster, and Uhrig-Homburg (2016). Computed as the difference between the 75th and 25th percentiles of transaction prices relative to the average price. Higher values indicate greater price dispersion and lower liquidity.	WRDS Bond Returns
(iii). Biodiversity risk exposure measures			
Count-based biodiversity exposure	*Count_Score*	An indicator variable equal to one if the firm's 10-K filing contains at least two biodiversity-related sentences identified using predefined regular expressions and a BERT-based classifier, following Giglio et al. (2026), and zero otherwise. This measure captures the presence of biodiversity-related discussion in corporate disclosures.	Giglio et al. (2026)
Regulation-based biodiversity exposure	*Reg_Score*	An indicator variable equal to one if the firm's 10-K filing contains at least two biodiversity-related sentences and at least one reference to biodiversity-related regulatory terms (e.g., law, regulation, Act, ESA, discharge, restriction), following Giglio et al. (2026), and zero otherwise. This measure captures biodiversity exposure associated with regulatory risk.	Giglio et al. (2026)
Negative-tone biodiversity exposure	*Neg_Score*	An indicator variable equal to one if the net biodiversity disclosure tone is negative, and zero otherwise. The underlying sentiment score is calculated as the difference between the number of negative and positive biodiversity-related sentences identified in the firm's 10-K filing using a BERT-based classifier, following Giglio et al. (2026). Firm-years with no biodiversity-related discussion or only neutral statements receive a score of zero.	Giglio et al. (2026)

Geographic biodiversity exposure	*logCBE30*	Log of one plus the corporate biodiversity exposure measure developed by Akbari, Ng, Pham, and Yu (2025), which captures the number of biodiversity-protected areas located within a 30-kilometre radius of the firm's operational sites. The establishment-level measure is aggregated at the firm-year level. Unlike text-based measures, CBE30 reflects firms' physical proximity to biodiversity-sensitive ecosystems.	Akbari et al. (2025)
(iv). Firm-level control variables			
Firm size	*log(MCAP)*	Natural log of market capitalisation, measured as share price times shares outstanding at the end of the fiscal year, lagged one year.	CRSP/Compustat
Market-to-book ratio	*log(MB)*	Natural log of the market-to-book equity ratio, defined as the market value of equity divided by the book value of equity at the end of the fiscal year, lagged one year.	Compustat
Stock return volatility	*log(Std_Ret)*	Natural log of the standard deviation of daily stock returns computed over the firm's fiscal year. Higher values indicate greater return variability.	CRSP
Analyst coverage	*ln_Analysts*	Log of one plus the number of sell-side analysts issuing earnings forecasts for the firm during the fiscal year.	I/B/E/S
Institutional ownership	*Total_IO*	Fraction of shares outstanding held by institutional investors, calculated from quarterly 13F filings and averaged over the fiscal year.	Thomson Reuters 13F
Inverse stock price	*1/Price*	Inverse of the year-end stock price. Included to control for the known relation between stock price level and measured illiquidity.	CRSP
Capital expenditure	*CAPXAT*	Capital expenditures scaled by total assets at the end of the fiscal year, lagged one year.	Compustat
Return on assets	*ROA*	Net income divided by total assets at the end of the fiscal year, lagged one year.	Compustat
R&D intensity	*RDat*	Research and development expenditures scaled by total assets at the end of the fiscal year. Missing values are set to zero.	Compustat
Advertising intensity	*Adat*	Advertising expenses scaled by total assets at the end of the fiscal year. Missing values are set to zero.	Compustat

Book leverage	*bklev*	Total debt (long-term debt plus debt in current liabilities) divided by total assets at the end of the fiscal year.	Compustat
Firm age	*logage*	Log of the number of years since the firm first appeared in the Compustat database.	Compustat
Tobin's Q	*Tobin Q*	Market value of assets divided by book value of total assets, where market value equals book assets minus book equity plus market equity.	Compustat
Asset tangibility	*Asset Tangibility*	Net property, plant, and equipment scaled by total assets at the end of the fiscal year.	Compustat
B. Bond-level variables			
(i). Bond characteristics			
Offering amount	*Offering Amount*	New-issue size of the bond divided by 1,000,000.	Mergent FISD
Coupon rate	*Coupon*	Annual coupon rate of the bond, expressed as a percentage.	Mergent FISD
Bond maturity	*Bond Maturity*	Number of years remaining until the bond's scheduled maturity date.	Mergent FISD
Bond maturity squared	*Bond Maturity*^{2}	Squared years to maturity, included to capture non-linearity in the relationship between maturity and illiquidity.	Mergent FISD
Bond age	*Bond Age*	Number of years since the bond's original issuance date.	Mergent FISD
Credit rating	*Credit Rating*	Combined numeric credit rating derived from S&P, Fitch, and Moody's on a scale from 1 (highest quality) to 25 (lowest quality).	Mergent FISD
C. Mechanism and identification variables			
(i). Institutional ownership and attention			
Change in institutional ownership	$\Delta Total_IO$	Year-over-year change in institutional ownership, calculated as institutional ownership in year t minus institutional ownership in year t − 1.	Thomson Reuters 13F
Lagged change in institutional ownership	$\Delta Total_IO_{t-1}$	One-year lagged annual change in institutional ownership.	Thomson Reuters 13F
Low analyst coverage	*Low_Coverage*	An indicator variable equal to one if the number of analysts covering the firm falls below the sample median in a given year, and zero otherwise.	I/B/E/S

Change in low coverage	*ΔLow_Coverage*	Year-over-year change in the low analyst coverage indicator, calculated as the low-coverage indicator in year t minus its value in year t − 1.	I/B/E/S
Lagged change in low coverage	$\Delta Low_Coverage_{t-1}$	One-year lagged annual change in the low analyst coverage indicator.	I/B/E/S
(ii). Difference-in-differences variables			
Treatment indicator	*Treated*	An indicator variable equal to one if the firm operates in a biodiversity-intensive industry (e.g., agriculture, mining, chemicals, construction, electric/gas/water supply), and zero otherwise. Industry classification follows Becker et al. (2025).	—
Post-event indicator	*Post*	An indicator variable equal to one for fiscal years 2011–2022, and zero for years prior to the 2010 Deepwater Horizon oil spill.	—
DID interaction	*Treated* × *Post*	Interaction of *Treated* and *Post*, capturing the differential change in liquidity for firms in biodiversity-intensive industries relative to control firms following the 2010 Deepwater Horizon oil spill.	—
(iii). First-difference variables			
Change in stock illiquidity	*ΔIlliqAM*	Annual change in the Amihud stock illiquidity measure, calculated as IlliqAM in year t minus IlliqAM in year t − 1.	CRSP
Change in bond illiquidity	*ΔIlliqRT*	Annual change in the round-trip bond transaction cost measure, calculated as IlliqRT in year t minus IlliqRT in year t − 1.	WRDS Bond Returns
Change in biodiversity risk	*ΔBiodiversity Risk*	Annual change in each of the biodiversity risk exposure indicators (*Count_Score*, *Reg_Score*, *Neg_Score*), calculated as the indicator value in year *t* minus its value in year *t* − 1.	Giglio et al. (2026)

Notes. This table defines the variables used in the empirical analysis. Panel A reports firm-level variables, including stock and bond liquidity measures, biodiversity risk exposure indicators, and firm-level controls. Panel B reports bond-level characteristics. Panel C reports variables used in the mechanism tests and the difference-in-differences identification strategy.