Indebted to Nature:

Corporate Biodiversity Endowment and Bond Market Reactions

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Abstract

Regulatory concerns of biodiversity conservation prompt creditors to markdown firms surrounded by rich wildlife species. Combining a proximity-based biological diversity endowment (BDE) measure with a plausibly exogenous shock to regulatory enforcement, we find support of increased regulatory concerns: After the shock, high-BDE firms experience a sharp rise in bond spreads and suffer disproportionately with less bond issuance. These firms also experience more post-shock curbs on business operations and a larger deterioration in firm fundamentals, confirming the transition risk channel. Finally, high-BDE firms' transition risk exposure is magnified by local regulatory intensity, but is not mitigated by their prior ESG performance. [100 words]

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It was a stroke of bad luck that the well happened to be located in the most species-rich part of the deep gulf. […] BP could not have selected a worse area to have a spill, at least from the point of species richness.

—Mark Schrope, "Oil Spill: Deep Wounds." *Nature*, 2011

1. Introduction

In the pursuit of industrialization and urbanization, biodiversity collapse is becoming more pressing worldwide, and it endangers the well-being of people and the planet (Cardinale et al., 2012; Stuart et al., 2000; Hooper et al., 2012; Isbell et al., 2015).[1] As a vivid example, Frank (2024) documents that the sudden decline of insect-eating bats across North America forces farmers to respond by substituting natural pest control (i.e., bats) with insecticides; however, because those are toxic compounds, by design, this substitution resulted in crop revenue deceases totaling $39.4 billion, and a 7.9% rise in infant mortality rates within US counties affected by bat die-offs. Similarly, in a recent American Economic Review paper, Frank and Sudarshan (2024) document that the functional extinction of vultures, a keystone species, increases human mortality by over 4 percent in India. In short, biodiversity collapse poses a real threat to human well-being and the economy. Yet, we still have a rather limited understanding of how biodiversity loss ends up affecting the microeconomic behavior of firms in the financial markets.

This paper aims to provide novel evidence on the broad impact of biodiversity loss, a specific form of environmental issues, on financial markets. We investigate whether societal and regulatory changes towards biodiversity conservation affect the pricing and contracting of corporate bonds. To date, biodiversity finance—the financial implications of biodiversity risk—is largely under-developed (Starks, 2023; Karolyi and Tobin-de la Puente, 2023). This under-development is mainly attributed to the following factors: First, there is a lack of relatively accurate and robust methods to quantify a firm's biodiversity exposure over time (Giglio et al., 2023). This may arise from the extensive time and resources required to conduct comprehensive scientific surveys on

[1] Between 1970 and 2018, the world has seen a 69 percent loss in monitored wildlife (WWF, 2022).

biodiversity. Second, biodiversity loss often arises from frequently overlooked human-related sources, such as noise pollution, which are not concentrated in "brown" industry alone. For example, Taylor and Mayer (2023) show that vessel noise and habitat degradation from port activities are strongly linked to the decline of the Southern Resident Killer Whale. Third, obtaining causal evidence on biodiversity risk is challenging since manipulating ecosystems is unethical and infeasible (see Frank and Sudarshan, 2024). Finally, biodiversity collapse and climate crisis are deeply intertwined, which makes it challenging to disentangle biodiversity risk from climate risk (Flammer, Giroux, and Heal, 2025).

To address these challenges, we start by proposing a novel firm-level biological diversity endowment (BDE) measure, which utilizes reliable scientific research data from eBird to summarize the ecological richness surrounding a firm.[2] Specifically, we calculate the bird species richness within a radius of 50 kilometers (km) surrounding a firm's corporate site to quantify its corporate biodiversity endowment. Bird species richness, derived from the spatial information of bird observations, is used extensively in scientific research to quantify the biodiversity of a certain region or geographical area (see Brodie et al., 2023; Valente et al.,2020; Redding et al., 2019; Knapp, 2011; Marris, 2010; Callaghan et al., 2021). Moreover, birds exhibit high vulnerability, and are adversely impacted by habitat degradation. The time variation of bird species richness is also widely employed by regulators as a primary indicator for evaluating biodiversity conservation efforts. For example, Streamlining European Biodiversity Indicators (SEBI) incorporates bird species richness to set the EU biodiversity targets.

Next, we investigate the impact of corporate biodiversity endowment on a firm's bond price and its debt financing conditions (i.e., bond origination). Our key identification assumption is that a firm's biological diversity endowment is positively correlated with

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[2] Note eBird (https://ebird.org/home) is the largest biodiversity-related science project worldwide. As a citizen-based bird observation database created and maintained by the Cornell Lab of Ornithology, it has recorded more than two billion bird observations across the globe, containing more than 97% of the World's bird species. It has an extensive coverage for China, recording bird species and their spatial distribution across provinces/cities in China.

its expected transition cost when there is increased regulatory pressure aimed at biodiversity conservation. High-BDE firms—those have a close proximity to rich wildlife species and diverse ecosystems—are, by construction, situated in a high-stakes natural environment from the perspective of regulators (i.e., the Ministry of Ecology and Environment). They are closely monitored by regulators, and are subject to more regulatory constraints on business operation, land use, and access to natural resources (i.e., the transition cost channel). Their higher transition risk (i.e., an unexpected cash flow shock due to the unforeseen regulatory shifts) may arise from legal fines or the costs of compliance in an increasingly demanding regulatory environment towards biodiversity preservation (Garel et al., 2024). For example, a high-BDE firm whose existing plant site endangers the nearby wildlife and their habitats might experience more operational disruptions due to (unforeseen) environmental and ecological inspections, and thus be more curbed on its land-use and expansion by revised environmental regulations in the future. Moreover, high-BDE firms are associated with more regulatory uncertainty, even if there are no immediate regulatory enforcement. In short, high compliance costs, combined with uncertainty associated with future biodiversity-related regulation or litigation, prompt creditors to perceive high-BDE firms as "more indebted to nature" than low-BDE firms, and thus demand a higher yield spread and attach more stringent debt financing conditions to these high-BDE firms.[3]

To address the identification challenges regarding the causal relation between corporate biodiversity endowment and debt financing conditions, we turn to the "Green Shield Action (GSA)" campaign, a major campaign-style regulatory enforcement aimed at countering biodiversity loss in China. In July 2017, the Chinese central government launched the GSA by carrying out massive-scale law enforcement inspections on nature reserves, targeting violations such as mining, tourism, and hydropower that threaten the wildlife and their habitats. During the campaign, the Chinese central government

[3] The theory by Pastor and Veronesi (2012) implies that uncertainty associated with future regulation or litigation leads investors to require a risk premium for holding less eco-friendly assets (such as brown stocks). Consistent with this prediction, studies show that investors demand compensation for exposure to carbon or pollution risks (Bolton and Kacperczyk, 2021, 2023; Hsu, Li, and Tsou, 2023).

utilizes a combination of advanced technology, such as high-resolution remote sensing images, drones, and a mobile monitoring application for nature reserves, to effectively identify environmental issues and violations. Moreover, the central government exerts its top-down political power to pressure the local authorities by holding more than 1,100 local officials accountable for the identified violations (Chen et al., 2024). In response, local authorities need to create and execute a detailed work plan that aligns with the guidelines set by GSA to address the environmental issues. By the end of 2017, it is reported that more than 2,460 illegal enterprises were shut down and over 5.9 million square meter illegal construction facilities were dismantled nationwide. In short, GSA represents an exogenous shock to firms' regulatory risk. Its high visibility and the massive financial costs incurred in environmental law enforcement serve as a wake-up call to the public regarding biodiversity transition risk, thereby increasing the relevance of corporate biodiversity endowment for creditors.

To exploit the shock to biodiversity transition risk, we adopt a standard difference-in-differences method to compare the yield spreads in the secondary market and bond contracting terms in the primary market of high-BDE firms with those of low-BDE firms before and after the implementation of GSA. We select 2017Q3 as the beginning of the treatment period because GSA is implemented in July 2017. For identification, we use pre-GSA levels of BDE, averaged over 2014Q1 to 2016Q4, as it is unlikely that firms adjusted their corporate biodiversity endowment in anticipation of the regulatory shock.[4] Because GSA is a plausibly exogenous event with respect to firms' pre-GSA BDE, our empirical strategy circumvents endogeneity concerns that arise in capital market responses to corporate biodiversity endowment.

Our results indicate that high-BDE firms are indeed perceived as more indebted to nature, and are treated less favourably by creditors after the implementation of GSA. Compared to low-BDE firms, there is a notable additional increase in bond spreads by

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[4] In fact, biodiversity (i.e., richness in wildlife species) is a public good requiring coordinated efforts from other stakeholders (i.e., regulators); Without external factors, such as regulatory pressure, a conventional firm has hardly any financial incentive to alter its surrounding ecological features alone.

66 basis points (bps) per annum for high-BDE firms in the treatment period. The economic magnitude of this spread increase is also substantial, which represents at least a 50% increase relative to the pre-GSA yield spread (i.e., the pre-GSA sample mean of yield spread is approximately 1.30% per annum).

Similarly, we document that high-BDE firms experience a sharp deterioration of debt financing conditions in the primary market. After this exogenous shock to transition risk, high-BDE firms also suffer disproportionately more in the primary market by issuing less debt, and at higher spreads.

To pinpoint the underlying mechanism through which biodiversity transition risk is incorporated into the bond market, we perform three sets of validation tests: Firstly, we show that GSA has real consequences for economic activities. Using both the nightlight luminosity (derived from remote sensing image) and thermal infrared radiation (TIR) to quantify a firm's land-use and business activities, we document that high-BDE firms indeed suffer a larger shrinkage of real economic activities than low-BDE firms after the implementation of GSA, as their nightlight luminosity and production-related TIR drop disproportionately more after 2017Q3. Secondly, we find collaborating evidence that heightened regulatory pressure stemming from the GSA campaign exerts an adverse impact on firm fundamentals. In particular, high-BDE firms suffer more greatly in their post-GSA financial performance—an additional reduction of 25% in their return on assets (ROA)—than their low-BDE peers after the implementation of GSA. Thirdly, we exploit the heterogeneity of regulatory intensity across regions to validate the transition risk channel. We argue that higher regulatory intensity amplifies creditors' concern over high-BDE firms' anticipated compliance costs relative to their peers. In line with our conjecture, we find that after the GSA campaign, it is mainly those high-BDE firms from regions under greater regulatory scrutiny that are bearing the disproportionately higher cost of debt capital than comparable high-BDE firms located in low regulatory intensity regions (i.e., a "triple difference" effect). In short, these validation tests confirm that firms endowed with ecologically diverse surroundings are more indebted to nature under a rigid biodiversity conservation regime (i.e., paying a higher price for transition). These effects are broadly in line with the risk-management hypothesis, which posits that in the presence of heightened uncertainty (Merton, 1973; Campbell, 1993, 1996), investors demand additional compensation for holding bonds associated with such risks (Addoum et al., 2019; Bali, 2008; Bali, Brown, and Tang, 2017; Bolton and Kacperczyk, 2023; Li et al., 2024).

Finally, we assess whether a firm's prior ESG performance could mitigate its exposure to biodiversity transition risk, as one might argue that biodiversity collapse and climate crisis are deeply intertwined (Flammer, Giroux, and Heal, 2025). Following the convention, we use the ESG (E) score to measure a firm's climate performance, and construct a high ESG (E) dummy that identifies firms with above-median climate performance. We document that the yield spread of high-BDE firms with a strong ESG score does not deviate from that of comparable high-BDE firms with a weak ESG performance after the GSA campaign, suggesting that solid (pre-event) ESG performance does not alleviate creditors' concern over a firm's exposure to biodiversity transition risk.

Our work contributes to three strands of literature: First, it adds to the broad literature on environmental risks and sustainability. In particular, our work advances the emerging literature on biodiversity finance in two main aspects: On the one hand, it highlights the financial implications of biodiversity conservation in corporate bond market. Prior work on biodiversity risk indicates that equity investors react to biodiversity-related corporate disclosures and monitor firms' biodiversity footprint (Giglio et al., 2023; Garel et al., 2024). For example, Giglio et al. (2023) show that returns of portfolios sorted on textual-based biodiversity risk measures covary positively with biodiversity news. Garel et al. (2024) document that investors revise downwards their valuation of companies with relatively large biodiversity footprint (i.e., a more adverse impact on biodiversity) following the Kunming Declaration and the Taskforce on Climate-related Financial Disclosure. We augment these studies by providing novel evidence that increased biodiversity-related regulatory pressure (the GSA event) has real consequences on a firm's business operation and financial performance: High-BDE firms—those surrounded by rich wildlife species—experience disproportionately more operational disruptions and suffers more greatly in firm fundamentals after the policy shock. Moreover, these firms also suffer a sharp increase in bond spreads and a greater deterioration in debt financing conditions in the primary market, which highlights the role of corporate diversity endowment on the pricing and financial contracting of corporate bonds.

On the other hand, we also offer a novel firm-level measure on corporate biodiversity endowment that integrates seamlessly the natural capital approach emphasized in Flammer et al. (2025). Measuring biodiversity exposure is complex and inherent challenging. One viable approach is to construct disclosure-based biodiversity measures that could quantify a firm's exposure to biodiversity risk (Giglio et al., 2023) or its adverse biodiversity performance by aggregating its environmental footprint related to land use, air and water pollution, and greenhouse gas emissions (Garel et al., 2024). These disclosure-based measures provide valuable insights regarding a firm's biodiversity-related performance, but are constrained by the disclosure quality of a firm as well as its suppliers and clients along the supply chain (see Garel et al., 2024; Rawson, Twedt, and Watkins, 2022). An alternative approach is to construct proximity-based biodiversity measures that leverage geospatial information. For example, Chen et al. (2024) use the existence of nature reserves within the geographical boundaries of a city to construct a city-level biodiversity measure to study the pricing pattern of municipal bonds. Our BDE measure falls into this broad class of proximity-based biodiversity measures by leveraging open-source scientific research data on biodiversity (eBird). It summarizes a firm's environmental and ecological features by quantifying richness in wildlife species surrounding a firm (Brock and Xepapadeas, 2003). It also leverages scientific insights that biodiversity exhibits geographically clustering patterns (Leclere et al., 2020), indicating that a firm's biodiversity exposure is concentrated in its immediate vicinity. For example, the 2010 Gulf of Mexico oil spill caused a significant biodiversity catastrophe primarily due to its occurrence in the most species-rich region of the gulf (Schrope, 2011). Besides, our BDE measure, which builds on millions of bird observations over time, are time-varying in nature.[5] This allows us to measure gradual ecological changes, capturing the outcome of biodiversity conservation over time (see **Figure 2** for the improvement of biodiversity after the GSA).

Second, our study also contributes to the bond pricing literature by showing the credit relevance of corporate biodiversity endowment. Existing studies on the environmental impact on bond market are concentrated on climate change (Seltzer et al., 2022; Painter, 2020; Huynh and Xia, 2020; Goldsmith-Pinkham et al., 2023; Dickerson, Mueller, and Robotti, 2023; Chava, 2014). Importantly, our findings highlight the role of corporate biodiversity endowment as a determinant of bond spreads, as firms with a rich natural capital (i.e., high-BDE firms) experience a more drastic increase in bond spreads. Moreover, biodiversity risk is distinct from climate risk, and the carbon emissions-oriented ESG performance cannot mitigate biodiversity transition risk when there are societal and regulatory changes towards biodiversity conservation.

Third, our study also complements the corporate finance literature on firms' debt financing conditions. Our evidence that high-BDE firms are forced to scale down their debt issuance and at a much higher yield spread after the implementation of GSA suggests that creditors factor in a firm's corporate diversity endowment in the primary market. Firms endowed with a rich natural capital are viewed as "more indebted to nature" and treated less favourably by creditors in times with heightened regulatory pressure and transition risk for biodiversity conservation.

2. Institutional Background and Empirical Predictions

China holds a large landmass, stretching from the eastern coast along the Pacific Ocean

[5] On the other hand, alternative biodiversity measure based on the number of nature reserves (i.e., protection zones) are usually time-invariant, and occasionally spikes (because the government adds new nature reserves or reduces existing ones on an irregular basis). Moreover, an increase in nature reserves may not, at the very beginning, indicate an improvement of biodiversity (i.e., an increase in natural capital), rather, it may indicate the exact opposite—a deterioration of biodiversity that requires more biodiversity preservation and efforts.

to the western borders with Central Asia. The country encompasses a wide range of geographical features (such as mountains, plateaus, deserts, and river basins) within its extensive territory and is rated as one of the most biologically diverse countries in the world: For example, China is ranked the third in the world for its richness of vascular plant species, after only Brazil and Colombia. As another example, there are a total of 138,293 recorded known species in China, representing 6.4% of the total number recorded worldwide. In particular, at least 1,376 known bird species are observed in China (see eBird). Besides, four out of the nine major flyways worldwide traverse China, and 81 out of 428 Asian protected areas dedicated to safeguarding migratory bird species are situated within its geographical borders. In short, among the mega-biodiverse countries in the world, China plays a pivotal role in the global ecological system.

2.1 Green Shield Action

Designation of Protected Areas (PAs), such as nature reserves and wetlands, is a key measure for safeguarding species and ecosystems globally. Since 1956 (with the establishment of its first nature reserve), the Chinese central government has established thousands of national nature reserves (NNRs) and parks. Moreover, it has been drawing up ecological “red line” areas to restrict human and industrial activity over about one-quarter of the country in recent years (see Mallapaty, 2020). For example, in Zhejiang province, a key manufacturing hub in China, nature reserves cover only 10% of the land, while ecological redline areas encompass 26.25% of its land. These NNRs and red line areas are established for their role in conserving biological diversity and ecosystems within the protected area and across the broader landscape (Brodie et al., 2023), as well as benefiting the overall wildlife population (Van Doren et al., 2017; Wauchope et al., 2022). However, the effectiveness of any designated PAs highly depends upon management practices implemented by the local (provincial and/or municipal) governments (Benítez-López et al., 2017). In fact, the tension between economic growth and biodiversity conservation is a long-standing and pervasive issue globally. China is no exception: In the pursuit of industrialization and urbanization, many PAs were ill-managed by local governments (to favor local business and land use), impairing their biodiversity conservation function. For example, the Helan Mountain Nature Reserve—a prioritized NNR established in 1982 for biodiversity conservation—perfectly exemplifies this challenge. Despite its NNR status, localized ecological degradation in the Helan Mountain remains a pressing issue. Excessive development and human disturbances, both within and surrounding the nature reserve, have led to a series of ecological crises, including climate aridification, rising snowlines, and grassland degradation.[6]

Recognizing the (potential) malpractices at the provincial and municipal level, in July 2017 the Chinese central government launched the "Green Shield Action (GSA)" campaign, a major regulatory campaign to curb illegal activities that pose significant threats to biodiversity within and around protected areas. During the GSA campaign between July and December 2017, the Chinese central government deployed multiple investigation teams to carry out massive-scale law enforcement inspections that cover all national nature reserves (and some ecological red line areas), targeting violations such as mining, tourism, and hydropower generation that threaten the wildlife and their habitats. To effectively identify environmental issues and violations, investigation teams and staff adopted a combination of advanced technology, such as high-resolution remote sensing images, drones, and a mobile monitoring application for nature reserves. Moreover, the central government also utilizes its political power to pressure the local authorities by holding more than 1,100 local officials accountable for the identified violations.[7] In response, local authorities need to create and execute a detailed work

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[6] See the report (in Chinese) posted in 2017Q3 on the local government's website in regard to the identified environmental and ecological issues during the GSA inspection:
https://sthjt.nx.gov.cn/ztzl/sthbdczg/201708/t20170809_3814553.html
It was reported that there were more than one million population lives within the nature reserves of Gansu and Qinghai provinces: http://www.xinhuanet.com/politics/2018-11/06/c_1123668061.htm

[7] The central government's top-down approach that combines centralized inspection teams with high-powered political incentives for local officials was shown to be effective in enforcing environmental regulation (see He et al., (2022) for China's endeavor for water protection in the early 2000s).

plan that aligns with the guidelines set by GSA to address environmental issues.

By implementing comprehensive inspections and enforcing stringent legal measures, the GSA campaign demonstrated remarkable efficacy in deterring ecological violations and promoting ecological restoration: By the end of 2017, it is reported that more than 2,460 illegal enterprises were shut down and over 5.9 million square meter illegal construction facilities were dismantled nationwide. In a follow-up press release, the Minister of the Ministry of Ecology and Environment (MEE) refer to GSA as “the largest-scale initiative since China had begun to establish its first nature reserve in 1956. It ended with the largest number of problems identified, the tremendous rectifications that ensued, and the toughest accountability of liabilities ever”. He also signaled that the central government would continue the efforts in subsequent years by implementing GSA 2018, GSA 2019, and etc.[8]

In short, the implementation of GSA in 2017 is a landmark event in China, reflecting its increased law enforcement for biodiversity conservation on a massive scale. The GSA campaign represents a plausibly exogenous shock to firms’ regulatory risk on biodiversity conservation, and serves as a wake-up call to the public to (properly) reassess the massive financial costs incurred, and will incur, in environmental law enforcement going forward. Moreover, by signaling sequential actions going forward (i.e., GSA 2018, GSA 2019, and etc), the central government solidifies the expectations regarding its commitment to protect biodiversity and nature reserves, thus re-shaping the financial market’s perception of the overall transition costs associated with biodiversity conservation (Chen et al., 2024).

2.2 Empirical predictions

Regulatory concerns about *increased* biodiversity conservation should have immediate relevance for the pricing and contracting of corporate debt instruments, because environmental compliance costs can significantly affect firms’ operating costs and cash

[8] Source: https://english.mee.gov.cn/News_service/Photo/201804/t20180410_434126.shtml.

flows. Moreover, uncertainty about future regulations, by itself, could increase the cost of capital via the channel of regulatory uncertainty (Pastor and Veronesi, 2012). This regulatory concern should vary in the cross section, and is more concentrated among firms with a greater proximity to biodiversity—those firms that possess a high biological diversity endowment, manifested as rich wildlife species and diverse ecosystems surrounding the corporate site—because they tend to be the main targets by regulators and are thus subject to more regulatory constraints on business operation, land use, and access to natural resources. That is, even if two firms have identical objective biodiversity performance (i.e., in terms of pollution and emission), the one that has a high biological diversity endowment is likely to subject to greater regulatory constraints than another firm that has a low biological diversity endowment. Therefore, we posit that the implementation of GSA disproportionately increases creditors' regulatory concern on high-BDE firms, and thus leads to an adverse impact on the credit spread of those firms in the secondary market.[9]

Hypothesis 1. *Firms with a high biological diversity endowment experience a greater increase in credit spread after the Green Shield Action.*

Similarly, we posit that the increased regulatory concern subsequent to the GSA event is also expected to exert a material influence on subsequent bond issuance in the primary market, manifested as a greater deterioration in bond contracting terms (i.e., reduced bond issuance amount, higher at-issue offering spreads, and shorter maturities) for high-BDE firms.

Hypothesis 2. *Firms with a high biological diversity endowment experience a greater deterioration in bond contracting terms after the Green Shield Action.*

[9] In the appendix, we employ a structural credit model to illustrate how biodiversity transition risk is incorporated into the bond market. Built on the key identification assumption that a firm's BDE is positively related to its regulatory and compliance cost, the structural credit model rationalize why high-BDE firms should experience a sharp increase in yield spread and a decrease in distance to default after the implementation of GSA.

3. Sample and Summary Statistics

3.1 Data description and variable construction

We carefully construct a panel dataset on corporate bonds by merging data from various sources. The bond data are sourced from CSMAR and RESSET financial databases, from which we retrieve the following: (i). Bond transaction information, including (daily) trading yield, trading date, residual maturity; (ii). Bond contracting terms and rating information, including bond issuer, coupon yield, issuance date, actual issuing volume, issuing rating, duration; (iii). Yield curve of China Development Bank (CDB) bonds on a daily basis. Financial report information on the bond issuers is retrieved from CSMAR database, via which we construct the issuer-level characteristics such as firm size and leverage. We focus on exchange-traded corporate bonds issued by publicly listed companies, and exclude municipal bonds (i.e., enterprise bonds), medium-term notes (traded in the interbank market), commercial papers, and other corporate bonds. We also exclude bonds that are issued by a non-public firm or a financial firm.[10]

Data on bird observations are retrieved from eBird, a widely used scientific research database of bird distribution and abundance. The raw eBird dataset includes bird species observed, and the exact location and date of bird sightings. We use the time and geospatial information from bird observations (matched with firm locations) to calculate the firm-level biological diversity exposure (BDE) measure over time (see later for variable definition on BDE).

After merging these datasets and applying the filter rules as specified in **Table A.2** in the appendix, our final "secondary market" sample consists of 1,122 corporate bonds from 532 corporate issuers covering the sample period from 2014Q1 to 2019Q4.

[10] We exclude medium-term notes traded in the interbank market, because the interbank market is initially aimed for major banks and large financial institutions only. Many institutional investors (including investment funds, wealth-management products (WMPs) and trust companies) do not have direct access to the interbank market until 2016 (see Amstad and He, 2019).

A. Biological diversity exposure (BDE)

Our main independent variable is the firm-level biological diversity exposure (BDE) based on the richness of bird species. Bird species are particularly suitable for our research for two key reasons. First, birds demonstrate extensive distribution and remarkable diversity, facilitating the collection of timely and comprehensive bird species data through citizen science projects such as eBird (e.g. Brodie et al., 2023; Valente et al.,2020; Redding et al., 2019; Knapp, 2011; Marris, 2010, Callaghan, Nakagawa, and Cornwell, 2021). Thus, bird observations provide us with essential time variation of a firm's corporate biodiversity endowment. Second, birds are "indicator species" of the ecological system. Birds exhibit high vulnerability and a significant likelihood of being impacted by habitat degradation (Ewers et al., 2024), which makes them a comprehensive and direct indicator of biodiversity loss resulting from human activities such as land use, and air and water pollutions. Thus, assessing biodiversity through the richness of bird species provides a simplified yet precise method (Johnson et al., 2024; Rosenberg et al., 2019).

We utilize time and spatial information contained in bird observations to quantify a firm's corporate biodiversity endowment on a quarterly basis. Specifically, we measure a firm's biological diversity exposure (BDE) within a *circled* geographical area with a total radius of 50 kilometers (km) that centers around the corporate site (headquarter). We are aware that using the registered headquarter address rather than the plant site address may introduce measurement errors in our analysis, but this works against us; that is, the effect we estimate will be closer to zero than they would be absent from the measurement errors.[11]

[11] In fact, the main plant site of a manufacturing firm cannot deviate from its official registration location; Otherwise, it faces disciplinary actions according to Chinese Company Law (see Chen et al., 2018). Our key results are indeed stronger among the subsample of manufacturing firms (see **Panel E** of **Table A.3** in the appendix).

Our choice of a radium of 50 km (or equivalently a 100 km diameter) follows closely the conventions in scientific literature: It corresponds to approximately an area of one degree change in latitude or longitude, the standard unit used to assess species richness in ecological studies (Orme et al., 2005; Stuart et al., 2004; Ceballos and Ehrlich, 2006).

Our BDE measure is a distance-weighted bird species richness measure. Based on the geographical proximity to the center, the entire circled area is further divided into five annulus zones, starting from Zone 1 covering the inner circle area within 10 km from the headquarter, to Zone 2 covering the circular ring-shaped area within 10 to 20 km from the headquarter, …, and to Zone 5 covering the circular ring-shaped area within 40 to 50 km from the headquarter. We apply a linearly decreasing weighting scheme on the five zones, and compute the distance-weighted sum of the number of bird species surrounding a firm as follows:

$$BDE_i = \sum_{z=1}^{5} w_z N_z, \qquad [3.1]$$

where N_z is the number of bird species within the z-th annulus area (zone), and w_z is its correspondent weight. The linear weights start with 0.25 for Zone 1 and decrease by 0.025 each time for the following zones (i.e., 0.225 for Zone 2, …, and 0.15 for Zone 5), so that the sum of the normalized weights equals one. The descending weighting scheme follows closely the intuition that the more proximity of a firm's corporate site to the abundance of wildlife, the higher the uncertainty of future biodiversity-related regulatory shocks it faces (i.e., higher BDE-related transition risk). **Figure 1** illustrates the distance-weighted BDE measure for a sample firm in our dataset.

[**Figure 1** around here]

B. Bond yield spread

Our main dependent variable is a bond's credit spread, which equals the difference between a bond's last daily trading yield of the quarter and the CDB yield matched by maturity on the same day (Geng and Pan, 2024). Note, to ensure our results are not driven by outliers, we winsorize bond spreads at the 1% and 99% levels, respectively.

Besides bond spreads, we also construct a set of bond- and issuer-level characteristics, including bond size, residual time-to-maturity, credit rating, puttable indicator, callable indicator, firm size, leverage, and return on assets (ROA). **Table A.1** in the appendix contains detailed definitions of those variables.

3.2 Sample and descriptive statistics

Our sample is quarterly based, which runs from 2014Q1 through 2019Q4. **Table 1** presents the summary statistics of the main variables, including bond spreads, bond and issuer features, and the firm-level BDE over the full sample period. The average bond spread amounts to 1.231% (1.564%) per annum in the secondary (primary) market. The mean of residual (at-issue) time-to-maturity is 3.303 (4.423) years. Following the convention in the literature, we convert the credit rating of a bond into a numerical value, starting from one for AAA, two for AA+, …, through eight for ratings below A. The mean bond rating of 1.936 indicates that an average bond in our sample tends to have an AA+ rating (or slightly above). In addition, most bonds are puttable, while only 7.9% of bonds are callable. The at-issue maturity in the primary market is slightly lower than that in the secondary market, because some bonds traded in the secondary market are issued before the sample period (i.e., less affected by the maturity decline after the GSA).

[**Table 1** around here]

We also split the sample into two subsamples (labelled as "Phase 1" and "Phase 2" subsamples) by using 2017Q2 as the cut-off date (i.e., the last quarter before the implementation of GSA). Phase 1 covers from 2014Q1 to 2017Q2 (inclusive), and

Phrase 2 runs from 2017Q3 through 2019Q4. **Table 2** presents the summary statistics of the main variables, including bond spreads, bond and issuer features, and the firm-level BDE for the two subsamples. In the secondary market, the average spread decreases slightly from 1.297% in Phase 1 to 1.188% in Phase 2, while the standard deviation increases from 1.412% to 1.644%. The average residual time-to-maturity falls from 3.545 to 3.019 years, and the at-issue time-to-maturity decreases from 5.931 to 5.360 years. The average credit rating improves from 2.128 to 1.710, indicating a higher credit quality on average. In the primary market, the average issue amount declines from 1.340 to 1.195 billion Chinese yuan after the GSA, and the at-issue maturity decreases by 0.692 years on average. Conversely, the average spread in the primary market rises from 1.520 to 1.603. Notably, while bond sizes in the secondary market slightly increase, the issue amounts in the primary market decrease. This divergence stems from an increase in at-issue maturity after Q1 2014 compared to earlier periods, followed by a significant decline in the post-GSA period for High-BDE firms.

[**Table 2** around here]

4. Corporate Biodiversity Endowment and Bond Market Reactions

4.1 BDE and yield spreads in secondary market

In this section, we seek to understand whether corporate biodiversity endowment impacts the pricing of corporate bonds. As is explained in **Section 2.2**, our central hypothesis (**Hypothesis 1**) is that high-BDE firms have a greater regulatory exposure, and thus face a higher cost of debt capital (i.e., credit spread) in an increasingly demanding regulatory environment regarding biodiversity preservation.

To validate our central hypothesis, we exploit the implementation of the "Green Shield Action" that aims to countering the depletion of biodiversity as a plausibly exogenous shock to transition risk. We employ a standard difference-in-differences (DID) approach as our baseline empirical strategy to examine the differential impact on bond yield spreads *before* and *after* the policy shock of GSA in 2017. The sample period spans from 2014Q1 to 2019Q4. The model specification is as follows:

$$Spread_{ijt} = \beta HighBDE_i \times Post_t + \sum \boldsymbol{Controls}_{ijt} + \boldsymbol{FE}s + \epsilon_{ijt}, \qquad [4.1]$$

where i, j, and t index the firm, bond, and time, respectively. The left-hand variable, $Spread_{ijt}$, denotes the yield spread of bond j issued by firm *i* in quarter *t*. $HighBDE_i$ is a dummy variable that equals one if a firm's pre-event BDE, estimated as the quarterly average between 2014Q1 and 2016Q4, is above the sample median (i.e., the treatment group), and zero otherwise. $Post_t$ is a dummy variable that equals one for the sample period after the introduction of GSA (i.e., from 2017Q3 onwards) and zero otherwise. We also control a wide range of bond- and firm-level characteristics ($\sum \boldsymbol{Controls}_{ijt}$), which includes bond size, credit rating, time to maturity, at-issue-maturity, callable feature, puttable feature, firm size, leverage, and return on asset (ROA). We also include different sets of fixed effects (***FEs***), capturing firm, location, and time dimensions, to control for unobservable credit risk factors. In particular, we include the city-by-quarter fixed effects to allow for the differential time trends across cities. Following Bonsall (2014), we cluster standard errors by firm to mitigate the effects of time-series correlation across bonds issued by the same firm.

The exogenous nature of the GSA helps alleviate the endogeneity concern with **Equation [4.1]**. The underlying assumption is that GSA is exogenous with respect to a firm's corporate biodiversity endowment. Most of a firm's natural capital is inherited from nature, and a firm has little economic incentive to alter its ecological surroundings. When the policy shock hits, the value of natural capital that the firm possesses (or inherited from nature) becomes more prominent.

The slope coefficient (β) on the DID term captures the differential responses between high-BDE firms and low-BDE firms after the GSA policy shock (i.e., the treatment effect). We expect β to be positive, reflecting the notion that firms with a higher biodiversity exposure are subject to more compliance costs in an increasingly demanding regulatory environment (i.e., a higher transition risk) than those with a lower biodiversity exposure. To account for that, creditors charge a relatively high yield spread on these risky bonds from high-BDE issuers.[12]

Table 3 presents the estimation results of our baseline analysis. In column (1), we only include firm fixed effects and city-by-quarter fixed effects. We then augment the model specification with bond-level controls in column (2), and with bond- and firm-level controls in column (3), respectively. As expected, the slope coefficients on the difference-in-differences term are highly positive, ranging from 0.663 to 0.674, and are statistically significant at the 1% level across the alternative model specifications. More crucially, it highlights the *differential* economic impact on firms' funding costs after the launch of GSA. Taking column (3) as an example, the estimates suggest that there is a 66-bps yield increase for corporate bonds issued by high BDE firms relative to those issued by low BDE firms *after* the exogenous GSA shock. This corresponds to a nearly 54% increase in debt funding costs relative to the full-sample mean (123 bps in **Table 1**). To put it into perspective, considering a typical bond with an average issuing amount of 1.4 billion Chinese yuan during our sample period, this 66-bps increase translates into an additional annual interest cost of 9.24 million Chinese yuan for the bond issuer.

[**Table 3** around here]

Robustness checks. Our key finding that high-BDE firms experience a sharp increase in credit spreads after the launch of the GSA inspection is robust to a variety of alternative empirical implementations: First, we test for a different set of fixed effects by using the bond fixed effects (in lieu of firm fixed effects) to purge time-invariant

[12] We are aware that there are two major concerns with this setting. First, it is possible that biodiversity transition risk may have already been priced prior to GSA. Second, there might have been expectations regarding GSA before its launch. We argue against these possibilities based on empirical findings presented in **Figure 3**. Prior to GSA, no significant differences in spread can be observed between the two groups; however, starting from 2017Q3, a significant difference emerges, indicating that GSA is not anticipated beforehand and bond markets begin to price in the biodiversity transition risk since its launching.

features associated at the bond level. Second, we implement the two-way clustered standard errors (i.e., clustered by firm and quarter). Third, we use the weighted least square (WLS) estimates to ensure the results are not unduly driven by issuer size. Fourth, we perform the analysis on subsamples, which exclude firms in Beijing, Shanghai, and Guangdong province, to ensure that the results are not unduly concentrated in these major cities and provinces. Rather, it reflects the trend of the broad market. Fifth, we focus on the subsample of manufacturing firms only, showing that the plausibly exogenous shock to biodiversity transition risk (i.e., the GSA event) indeed have a substantial financial impact on the manufacturing firms. Sixth, we adopt the propensity score analysis of difference-in-differences estimates, the approach outlined in Bonsall (2014), to alleviate the concern that the treatment group (i.e., high-BDE firms) may differ systematically from the benchmark group (i.e., low-BDE firms) in certain issuer-related characteristics. In all cases, our key findings continue to hold (see **Panels A** to **F** of **Table A.3** in the **Appendix**).

In addition, we also check for default probability of the bond issuers. Consistent with the widening of credit spreads after the GSA shock, we observe an increase in implied default probability, as the Bharath and Shumway (2008) distance to default (DD) measure for High-BDE firms declines significantly following the implementation of GSA (see **Table A.4** in the **Appendix**).

Overall, these findings provide strong support for **Hypothesis 1**, and they illuminate the fact that biodiversity transition risk is incorporated in the pricing of credit market, resulting in a sharp rise in firms' cost of debt capital after the GSA shock.

4.2 Address the industry effect

One legitimate concern is that our documented spread-BDE relation might be a pure manifestation of the industry effect, as biodiversity-related exposure differs across industries (Giglio et al., 2023). We argue, however, that the industry effect is unlikely to be the main contributor to our findings for the following reasons: First, our firm-level

BDE measure accurately pinpoints the geospatial properties of a firm, as opposed to its industry classification. There is no strong reason to assume that the proximity to rich wildlife species (i.e., the geospatial properties) is highly correlated with industry classification. Second, a high-BDE firm that has closer proximity to wildlife and their habitats would have a disproportionately large adverse impact on biodiversity, and thus receive greater regulatory pressure and investor scrutiny than another near-identical firm within the same industry but is far from wildlife and nature (i.e., a low-BDE firm). In other words, our BDE measure is capable of capturing the within-industry difference in biodiversity exposure across firms.

To address the concern of industry effects, we proceed with two empirical approaches. First, we remove the industry-specific effect by calculating the adjusted spread. The adjusted spread is defined as the difference between a bond's yield spread in quarter t and the median spread of the issuer's industry over the same quarter (in percentage points). That is, we remove the dynamic industry effect (i.e., the industry-specific component that might vary over time) from a bond's yield. We then use the adjusted spread as the dependent variable and re-run our panel regression model specified in **Equation [4.1]**.

[**Table 4** around here]

Table 4 presents the estimation results with adjusted spreads. As expected, after removing the industry effect, the slope coefficients on the difference-in-differences term are still highly positive, ranging from 0.590 to 0.593, and are statistically significant at the 5% level across all model specifications. This confirms that the industry effect is not a main contributor to our documented spread-BDE relation. Even if two firms are from the same industry, the high-BDE firm, on average, experiences a nearly 60-bps increase in bond spread after GSA than its low-BDE counterpart.

Second, we perform a falsification test by using the industry-level high-BDE dummy in lieu of the firm-level high-BDE dummy to re-run the regression model specified in **Equation [4.1]**. The industry-level high-BDE dummy equals one if a firm operates in a high-BDE industry (defined as its industry-level BDE exceeds the median BDE across all industries), and zero otherwise. If our documented spread-BDE relation is indeed a pure manifestation of the industry effect, then the slope coefficient on the difference-in-differences term should get stronger (i.e., because the industry-level BDE would be a cleaner measure while the firm-level BDE would be a very coarse measure in that setting) and highly positive with the industry-level high-BDE dummy. However, we do not find any support for the industry effect (see columns (1) to (3) in **Table A.5** in the appendix). In all cases, the slope coefficient on the difference-in-differences term is statistically insignificant and fairly small in magnitude as compared to its counterpart with the firm-level high-BDE dummy (refer to columns (1) to (3) in **Table 3**).

Overall, these results indicate that industry effect is unlikely to be the main contributor of our documented strong spread-BDE relation in the cross section. Even if two near-identical firms are in the same industry, as long as their BDE measures differ (i.e., implying different levels of biodiversity-related transition risk between the two firms assessed by creditors), their bond spread would differ.

4.3 BDE and bond origination

In this section, we validate whether high-BDE firms experience a greater deterioration in bond contracting terms in the primary market after the implementation of Green Shield Action (**Hypothesis 2**). In theory, the implementation of GSA should not impact existing bonds in the secondary market alone. Rather, it should also exert a substantial impact on subsequent bond issuance in the primary market as well. Following the convention in the literature (Amiraslani et al., 2022), we investigate three key aspects related to bond originations and contractual terms: Namely, scaled bond size, at-issue spread, and at-issue maturity. To do this, we retrieve all issuance data for corporate bonds issued between 2014Q1 and 2019Q4 from CSMAR and RESSET. After merging with issuer features, our "primary market" dataset comprises 834 bonds issued by 390 firms.

Similar to our baseline analysis in **Section 4.1**, we employ a difference-in-differences (DID) approach to examine the differential impact on bond contracting terms *before* and *after* the implementation of GSA. The model specification is as follows:

$$Y_{ijt} = \beta HighBDE_i \times Post_t + \boldsymbol{FEs} + \epsilon_{ijt}, \qquad [4.2]$$

where the dependent variable (Y_{ijt}) is bond issuing terms, such as the issuing amount (scaled by total asset), at-issue spread, and at-issue maturity. $HighBDE_i$ is a dummy variable that equals one if a firm's pre-event BDE, estimated as the quarterly average between 2014Q1 and 2016Q4, is above the sample median (i.e., the treatment group), and zero otherwise. $Post_t$ is a dummy variable that equals one for the sample period after the introduction of GSA (i.e., from 2017Q3 onwards) and zero otherwise. We also include different sets of fixed effects, capturing firm, location, and time dimensions. Following Bonsall (2014), we cluster standard error by firm to mitigate the effects of time-series correlation across bonds issued by the same firm.

[**Table 5** around here]

Table 5 presents the estimation results of **Equation [4.2]**. Firstly, when the dependent variable is the scaled bond size (in percentage points), defined as the bond issuing amount divided by the total asset of the bond issuer, we find that the DID coefficient is highly negative and statistically significant at the 1% level (see **column 1** of the table). This indicates that after the exogenous shock to transition risk, high-BDE firms face a tougher debt financing condition, as they are less able to raise *new* debt capital from the creditor. The economic magnitude of this shrinkage is also striking: High-BDE firms cut their issuing amount by a further 3.29 percent relative to their total asset value (see **column 1**), which drastically reduces their ability to use debt (corporate bonds) to raise capital from the market. We interpret this reduction in corporate bond issues after the

GSA shock as the "intensive margin", and we also check for the "extensive margin", defined as the denial of debt financing to firms, by running a linear probability model (with the same DID setting and fixed effects) on the issuance dummy that equals one if the firm issues a bond at any time during quarter t, and zero otherwise. As expected, after the GSA shock, high-BDE firms are 21.8 percent more likely to experience a denial in the primary market, as they can no longer renew an existing bond or issue a new bond (see **Internet Appendix** for more detail).

Secondly, we examine the results with the at-issue yield spread as the dependent variable (see **column 2** of the table). Similar to our definition of the yield spread in the secondary market, we calculate the at-issue spread as the difference between the coupon rate of a bond and Chinese development bank bonds' yield on the same day with the same maturity (in percentage points). The DID coefficient on the interaction between the high BDE dummy and Post dummy has the expected positive sign and amounts to 0.83, confirming the deterioration of at-issue bond spread in the primary market. This corresponds to an approximately 53% rise in debt financing costs (compared to the sample mean in **Table 1**). Although the DID coefficient is not statistically significant, the economic magnitude of this sharp rise in at-issue-spread (i.e., 53% increase) for high-BDE firms is similar to its counterpart estimated from the secondary market (i.e., 54% increase in **Table 3**), which re-assures our key findings that high-BDE firms are treated less favorably by creditors after the exogenous shock to biodiversity transition risk. On average, high-BDE firms have to bear an additional increase of 83 bps per annum when issuing new bonds after the implementation of GSA. The economic magnitude of the increase in at-issue yield spread is largely in line with that in the secondary market (see **Section 4.1**).

Lastly, we check for the impact on bond maturity at issuance. Prior research shows that bond maturity is adversely linked to systematic risk and uncertainty (Chen, Xu, and Yang, 2021), and bond issuers have limited capacity to renegotiate these terms, but to cater to creditors' demand (Amiraslani et al., 2022). If High-BDE firms are more exposed to biodiversity-related transition risk and treated less favorably by creditors, we expect these firms (relative to their low-BDE peers) to issue bonds with shorter maturities after the implementation of GSA, implying a negative coefficient on the interaction between the high BDE dummy and Post dummy. The estimation results confirm our notion with a DID coefficient amounts to –2.18, though it is not statistically significant. Following the implementation of GSA, the at-issue bond maturity indeed decreases for high-BDE firms relative to low-BDE firms (see **column 1**), which reflects that high-BDE firms face much tougher funding conditions than low-BDE firms after sudden unexpected shocks in biodiversity-related transition risk in bond market.

In a nutshell, these findings collectively support **Hypothesis 2** that high-BDE firms suffer disproportionately more in the primary market by issuing less debt, at higher spreads, and for shorter maturities after the exogenous shock to transition risk. In other words, high-BDE firms are treated less favorably by creditors than their low-BDE peers after the implementation of GSA.

5. Economic Mechanisms

So far, our results indicate that after the plausibly exogenous shock to transition risk, high-BDE firms are viewed less favorably than low-BDE firms by creditors. In this section, we further explore the heterogeneity across firms (bond issuers) to shed light on the underlying mechanism(s) through which biodiversity-related transition risk is incorporated into the bond market.

5.1 Real impact: Economic activities

In this subsection, we investigate the real economic consequences imposed by the GSA-related law enforcement on firm operations. In principle, high-BDE firms are usually situated in areas with rich wildlife species and ecosystems. Their possession of a higher abundance of natural capital and closer proximity to wildlife species and habitats make these firms an "easy" target by regulators. Consequently, these firms are subjected to more restrictions on their land-use (i.e., no site expansion and/or relocation of the existing site) and operational activities, implying a higher cost of compliance.

To validate the above conjecture, we utilize two sets of remote sensing satellite data. First, we follow Kalnay and Cai (2003) by calculating the nightlight luminosity—derived from remote sensing images (i.e., satellite data)—as a valid proxy of the land-use and economic activities surrounding a firm. We measure a firm's nightlight luminosity within a circled geographical area with a radius of 5 km that centers around the corporate site (headquarter).[13] Second, we employ thermal infrared radiation (TIR) data within a 5-km radius around the corporate headquarters to estimate a firm's operational intensity. Using the algorithm developed by Ermida et al. (2020), we calculate production-related TIR by subtracting natural TIR from observed TIR.[14] These two dependent variables enable us to capture real-time changes in a firm's operational scope and intensity. A low value of nightlight luminosity or TIR indicates that a firm is experiencing more restrictions on its land-use and possibly more frequent operational disruptions, and vice versa. To assess the real impact of the GSA, we conduct a difference-in-differences analysis to determine whether high-BDE firms experience disproportionately large reductions in nightlight luminosity and TIR following GSA implementation.

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[13] Nightlight intensity data are sourced from the Earth Observation Group (Elvidge et al., 2013) with a spatial resolution of 0.5 km × 0.5 km (0.25 km^2 per pixel). We adopt a 5 km radius to measure nightlight luminosity for two main reasons. First, a smaller scale generally reduces errors in capturing the luminosity of nearby firms compared to a larger scale, and a 5 km radius aligns with the typical operating area of listed firms (approximately 2 to 5 km). Second, a 5 km radius, encompassing a circular area of approximately 314 pixels, is the smallest scale that reduces the relative error to around 5%. Under the assumption of random noise, the standard error of the regional mean scales with the inverse square root of the number of aggregated pixels (Cressie, 1993). Thus, the relative error, calculated as $1/\sqrt{314}$, is around 5%, ensuring robust luminosity estimates for financial analysis.

[14] Thermal infrared radiation (TIR) data are sourced from Google Earth. The observed factory TIR encompasses both production-related TIR and TIR influenced by seasonal and regional factors. To isolate a firm's production-related TIR, we subtract the natural TIR from the observed TIR, following the methodology outlined in Ermida et al. (2020). The TIR is measured in Kelvin, where a decrease of one Kelvin corresponds to a one-degree Celsius reduction.

[**Table 6** around here]

Table 6 confirms this notion. As expected, in Column (1), the slope coefficient on the differences-in-difference term is highly negative and statistically significant at the 5% level, indicating that after the implementation of GSA, high-BDE firms indeed experience disproportionately more curbs on their land-use, manifested as the reductions in nightlight luminosity (i.e., more operational disruptions). More strikingly, the real impact imposed by the GSA-related law enforcement on high-BDE firms' operations is indeed sizeable, as the negative DID coefficient (–4.114) represents a sharp decrease of approximately 20% in nightlight luminosity relative to the sample median. Similarly, Column (2) indicates that, following the implementation of GSA, high-BDE firms experienced an average reduction of 2.844 degree Celsius in production-related TIR, reflecting a decline in their operational intensity. This strengthens the transition risk channel, as it provides direct evidence that high-BDE firms are subject to more hefty restrictions on their land-use and operational disruptions after the GSA-related regulatory shock.

5.2 Real impact: Fundamental performance

In this section, we explore whether the sudden increase in biodiversity transition risk led by the GSA campaign translates into the deterioration of financial performance in the cross section. In particular, we hypothesize that high-BDE firms are subjected to disproportionately high compliance costs (i.e., curbs on land-use, penalties, and operational disruptions) during the GSA campaign, which subsequently impairs their financial performance relative to low-BDE firms.

We adopt an event study approach to validate the link between (pre-event) corporate biodiversity endowment and (post-event) performance deterioration in the cross section. Specifically, we set 2017Q3 as the event date t and compute the post-event change in quarterly return on assets (ROA) as follows:

$$\Delta ROA_{i,t+\tau} = ROA_{i,t+\tau} - \overline{ROA}_{i,preGSA}, \quad [5.1]$$

where i denotes the issuer, t is the GSA event date (i.e., quarter) fixed at 2017Q3, τ marks the number of quarters after t, and $\overline{ROA}_{i,preGSA}$ is the pre-event ROA averaged across 2014Q1 to 2017Q2 to smooth out seasonality in the quarterly ROAs. $\Delta ROA_{i,t+\tau}$ captures firm i's change in fundamental performance of realized τ quarters after the event.

To formally estimate the performance difference between high-BDE and low-BDE firms after the GSA campaign, we gradually add up τ from 1 to 9 and perform the following panel regression:

$$\Delta ROA_{i,t+\tau} = \alpha + \beta HighBDE_i + \lambda Size_{i,t} + FEs + \varepsilon_{i,t+\tau}, \quad [5.2]$$

where $HighBDE_i$ is the pre-event high-BDE dummy defined the same as in **Section 4.1**, and the slope coefficient β is the difference-in-difference estimate in our event-study setting that captures the differences between high-BDE and low-BDE firms in their changes in ROA after the shock. $Size_{i,t}$ is the lagged total assets of the bond issuer. We add quarterly fixed effects to control the market-wide trend in ROA over time. We also add industry fixed effects to control the systematic differences in performance across industries. Note when τ equals one, it reduces to a cross-sectional regression.

[**Table 7** around here]

Panel A of **Table 7** presents the estimation results of the panel regression specified in **Equation [5.2]**. As expected, the slope coefficient on the high BDE dummy is highly negative and statistically significant at the 1% level over τ from 1 to 10, which confirms the strong link between pre-event corporate biodiversity endowment and post-event performance deterioration in the cross section. More importantly, the deterioration in ROA is also sizeable in economic terms for high-BDE firms (relative to low-BDE firms): On average, high-BDE firms' ROA experiences an additional drop ranging from –1.187% to –1.459% over the first one to nine quarters after the event (i.e., τ from 1 to 9), as measured by the difference-in-difference estimate. This accounts for more than 30% reduction in profitability for an average firm in our sample (i.e., the full-sample mean and median of quarterly ROAs are approximately 3.41% and 3.06%, respectively). We also find similar patterns when using return on equity (ROE), an alternative firm fundamental constructed similarly as in **Equation [5.1]**, as our dependent variable (see **Panel B** of the table).

In short, we find strong evidence that the shock to biodiversity transition risk, manifested by the GSA event, has a real impact on firm fundamentals. In particular, High-BDE firms endowed with rich ecological features and diverse ecosystems are predictably to suffer more greatly in their financial performance after the implementation of the GSA event.

5.3 Compliance cost: Regional heterogeneity in regulatory pressure

In this section, we exploit the regional heterogeneity in regulatory pressure to shed light on whether more intensive regulatory enforcement leads creditors to demand a higher yield spread for impacted firms. In theory, stricter regulatory intensity exacerbates a firm's regulatory burden by increasing the chances of financial penalties, operational disruptions, and mandatory remediation efforts. This heightened regulatory pressure signals to investors an elevated risk of financial instability, which adversely affects the pricing of corporate bonds (i.e., a wider yield spread).

As observed by Seltzer et al. (2022), the intensity of regulatory enforcement varies across regions, and the associated adverse impact on bond prices should be more pronounced for firms located in regions with more rigorous environmental oversight (Bolton and Kacperczyk, 2023). Seltzer et al. (2022) use the averaged U.S. Environmental Protection Agency (EPA) penalties in a state to quantify regulatory stringency of a given year. In a similar vein, we manually collect the number of accountable officials, those local officials who were publicly criticized and held accountable for "typical problems found in the GSA-related environmental inspections throughout 2017" within each province, to quantify the regulatory burden.[15] We normalize the by-region number of accountable officials by the provincial GDP in 2016 to make it comparable across firms. We posit that firms situated in regions under greater regulatory scrutiny—more accountable officials on a per unit GDP basis—face a higher transition cost, as their land-use and operational activities are likely to be disrupted more due to more intensive and frequent environmental inspections. That is, the widening of bond spreads should be larger for these impacted firms that are under greater regulatory scrutiny.

Specifically, using this normalized metric on regulatory intensity, we validate whether creditors are capable of differentiating firms that are bearing a high regulatory burden from other firms that are under less scrutiny. We define a high regulatory intensity dummy (denoted as Tightness) that equals one if the normalized metric is above the median, and zero otherwise. Using the bond spread as the dependent variable, we then test a "triple-differences" effect by allowing the firm-level Tightness dummy to interact with the High-BDE dummy and the Post dummy as defined in our baseline analysis. The model specification is as follows:

$$Spread_{ijt} = \beta_1 HighBDE_i \times Tightness_i \times Post_t$$
$$+\beta_2 HighBDE_i \times Post_t + \beta_3 Tightness_i \times Post_t \quad [5.3]$$

[15] Note there is a near-singular relation between the number of identified cases and the number of accountable officials in our data. Whichever of the two we use as our regulatory intensity proxy, our empirical results on bond spreads remain the same. We manually collect the information from Ministry of Ecology and Environment (MEE) and news releases.
The factors driving regional differences in environmental regulation enforcement differ markedly between China and the United States. In the U.S., variations arise from state-level autonomy in enforcement and economic incentives, often resulting in a "race to the bottom", where states compete by relaxing regulations to attract businesses (Konisky, 2007). In contrast, China's regulatory intensity variations stem from the central government's strategic allocation of enforcement efforts. Under this centralized system, the state prioritizes regions based on environmental or economic significance, directing more frequent and rigorous inspections to ecologically critical areas while applying less scrutiny to regions of lower priority. Thus, unlike the U.S., where enforcement disparities emerge from decentralized decision-making, China's regulatory differences reflect deliberate centralized choices regarding inspection intensity.

$$+\sum \boldsymbol{Controls}_{ijt} + \boldsymbol{FEs} + \epsilon_{ijt},$$

where we also control the other interaction terms, bond- and firm-level controls, and fixed effects as well. Note *HighBDE*, *Tightness*, and their interaction term (*HighBDE*× *Tightness*) are all firm-level dummies which are absorbed by the firm fixed effects (and thus omitted from the model specification).

[**Table 8** around here]

Table 8 presents the estimation results of the "triple-differences" model in **Equation [5.3]**. As expected, we document a strong "triple-difference" effect, as the slope coefficient on the double interaction term amounts to 61 bps (in **column 3**), which is highly positive and large in economic magnitude. This confirms our notion that creditors indeed charge a higher yield spread on high-BDE firms that are located in high-regulatory-intensity regions than comparable high-BDE firms from low-regulatory-intensity regions. In comparison, once we add this "triple-differences" term, the slope coefficient on our main DID term (HighBDE×Post) gets much smaller in magnitude (41 bps in **column 3**) and becomes statistically insignificant. This implies that it is mainly these high-BDE firms from regions under greater regulatory scrutiny that are bearing the disproportionately large financial burden (i.e., a higher cost of debt capital) after the exogenous shock to transition risk.

In short, we find compelling evidence on the transition risk channel that creditors carefully scrutinize a firm's corporate biodiversity endowment as well as its location-based regulatory intensity (Tightness). Comparable high-BDE firms located in regions that are under more regulatory scrutiny, manifested by a higher number of accountable local officials (per unit of GDP) during the GSA-related environmental inspections, are treated less favorably by creditors, resulting in a higher bond spread after the shock to transition risk.

5.4 Compliance cost: Could ESG performance mitigate biodiversity transition risk?

In this subsection we address two remaining, closely related questions on: (1) Do investors perceive biodiversity risk and climate risk differently? (2) Does a firm's prior, solid ESG performance help mitigate its exposure to biodiversity transition risk (i.e., alleviating the compliance cost)?

So far, we have established that high-BDE firms are treated less favorably by creditors after the implementation of GSA, an exogenous shock to biodiversity transition risk. But it remains unclear whether investors treat biodiversity risk and climate risk differently or simply associate them together (as one uniform environmental risk). On the one hand, biodiversity collapse and climate crisis are deeply intertwined (Flammer, Giroux, and Heal, 2025), as revised environmental policy and technical applications that address climate crisis tend to improve biodiversity as well.[16] On the other hand, biodiversity risk and climate risk are two different concepts that have visibly distinct environmental "symptoms": a decrease or even extinction of wildlife species vis-à-vis an increase of average temperature that leads to global warming. Therefore, Giglio et al. (2023) posit that investors treat them as two distinct risks.

To validate these competing views, we perform a counterfactual difference-in-differences test by treating the Paris agreement (i.e., the treaty is entered on 12 December 2015 in Paris) as a placebo shock to biodiversity risk. Bolton and Kacperczyk (2023) document that the Paris agreement raises investor awareness on climate risk, and it has a material impact on financial markets: There exhibits a large "green premium" right after the Paris agreement in December 2015 across international markets, and China is no exception. If biodiversity risk and climate risk are deeply connected, we should expect the Paris agreement to raise investor awareness on biodiversity risk, and high-BDE firms should experience a disproportionately large increase in bond spread

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[16] However, there are also some subtle and more technical reasons that certain technical applications, such as wind turbines, which alleviate climate risk, unintendedly amplify biodiversity risk (see Meng et al., 2025).

similarly as in the GSA event. Therefore, we perform a similar DID test as in **Equation [4.1]** with the following modifications: First, the *HighBDE* dummy is measured as the quarterly average in 2014, the pre-event time before the Paris agreement, to mitigate the endogeneity issue. Second, the $Post_t$ dummy equals one for the sample period after the Paris agreement (i.e., from 2015Q4 onwards), and zero otherwise. Third, the sample period is restricted from 2014Q1 to 2017Q2 to avoid contamination by the GSA event (from 2017Q3 onwards).

Table 9 presents the estimation results of the counterfactual test. We find no evidence that the Paris agreement increases investor awareness on biodiversity-related transition risk, as the slope coefficient on the DID term is indistinguishable from zero. This suggests, at least empirically, that investors do not associate biodiversity risk with climate risk (as one uniform environmental risk). Otherwise, we should observe a large positive coefficient on the DID term, indicating a larger bond spread for high-BDE firms following the entry of the Paris agreement.

[**Table 9** around here]

Next, we investigate whether a firm's prior ESG performance could mitigate its exposure to biodiversity-related transition risk, and thus alleviate the compliance cost. Prior research shows that solid ESG performance (i.e., a high ESG or E score) can act as a hedge against a firm's climate risk (See Engle et al., 2020; Amiraslani et al., 2022). Moreover, Garel et al. (2024) shows that carbon and greenhouse emission contributes to around 20% of corporate biodiversity footprint (e.g. 19.96% in China and 21.36% in the United States), suggesting that there is a natural, positive link between a firm's ESG (Environmental) performance and its biodiversity-related performance. In that sense, it is possible that creditors charge a low yield spread on firms with a high ESG (E) score, as they might perceive those firms to also have a solid performance in terms of biodiversity conservation, which mitigates the biodiversity transition risk induced by the GSA campaign.

To validate this notion, we utilize the Bloomberg ESG (E) scores and generate a High-ESG (High-E) dummy that equals one if a firm's pre-event ESG (E) score, averaged across 2014 to 2016, is higher than the sample median of all unique firms over the same period. Next, using the bond spread as the dependent variable, we then test a "triple-differences" effect by allowing the High-ESG (High-E) dummy to interact with the High-BDE dummy and the Post dummy. The model specification is as follows:

$$\begin{aligned} Spread_{ijt} &= \beta_1 HighBDE_i \times HighESG_i \times Post_t \\ &+\beta_2 HighBDE_i \times Post_t + \beta_3 HighESG_i \times Post_t \\ &+ \sum \boldsymbol{Controls}_{ijt} + \boldsymbol{FE}s + \epsilon_{ijt}, \end{aligned} \tag{6.1}$$

where we also control the other interaction terms, bond- and firm-level controls, and combinations of fixed effects as well. Note *HighBDE*, *HighESG*, and their interaction term (*HighBDE*×*HighESG*) are all firm-level dummies which are absorbed by the firm fixed effects (and thus omitted from the model specification).

[**Table 10** around here]

Table 10 presents the estimation results of the "triple-differences" effect. We find no evidence that a firm's high ESG (or E) score can mitigate the biodiversity-related transition risk, as the coefficient on the triple-difference term is insignificant. That is, creditors do not associate a firm's solid climate-related performance as a valid reference in addressing the sharp rise in biodiversity transition risk (led by the GSA event).

In a nutshell, we find collaborating evidence as in Giglio et al. (2023) that biodiversity risk is distinct from climate risk. Moreover, we document that a firm's prior ESG performance cannot mitigate their exposure to biodiversity transition risk.

6. Conclusion

Biodiversity loss poses a real threat to our planet and human society, and it has dire consequences on human well-being and the economy. In this paper, we explore the financial implications of biodiversity conservation in the corporate bond market.

Quantifying a firm's biodiversity risk exposure is inherently challenging. We propose a novel firm-level biological diversity endowment (BDE) measure, which follows from the generic definition of biodiversity (i.e., the variety of species, genetic diversity within species, and the ecosystems) by measuring the richness of bird species surrounding a firm. Our BDE measure focuses exclusively on a firm's corporate biodiversity endowment, the abundance of wildlife species and ecosystems surrounding the firm. It differs from existing textual analysis-based biodiversity measures that are often constrained by a firm's information disclosure quality.

We exploit the "Green Shield Action (GSA)", a major regulatory change aimed at countering biodiversity loss in China, as a quasi-natural setting to obtain causal evidence on how biodiversity transition risk is incorporated into the bond market. We find that firms endowed with rich wildlife species are viewed less favorably by creditors after this plausibly exogenous shock to transition risk: After the implementation of GSA, high-BDE firms experience a higher cost of debt capital than low-BDE firms. They also suffer disproportionately more in the primary market by issuing less debt and at higher spreads. These effects are in line with the transition risk channel, as high-BDE firms are subject to more regulatory pressures on land-use and business activities near the wildlife habitats, and suffer more greatly in their financial performance (such as ROA and ROE). Moreover, we also document that investors perceive biodiversity risk and climate risk as two distinct risks, and a firm's prior ESG performance does not mitigate its exposure to biodiversity transition risk.

Our findings have policy implications. Countering biodiversity loss requires drastic shifts in conservation efforts with substantial costs. Although most of the conservation costs are borne out by the government, private sector (i.e., firms) also bear a substantial fraction indirectly. In particular, these high-BDE firms that are endowed with a high abundance of wildlife species and ecosystems are likely to become disproportionately more "indebted" by bearing a higher compliance cost (or experiencing a greater disruption in their business operations) during this process when there is increased societal and regulatory pressure.

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Figure 1. Illustration of a firm's BDE measure

The figure illustrates the distance-weighted biological diversity endowment (BDE) measure of a sample firm (ticker: 002121). We measure a firm's bird species richness within a *circled* geographical area with a total radius of 50 kilometers (km) that centers around the corporate site (GPS: 22° 32' 55.33" N; 113° 56' 6.077" E). Based on the geographical proximity to the center, the entire circled area is further divided into five annulus zones, starting from Zone 1 covering the inner circle area within 10 km from the headquarter, to Zone 2 covering the circular ring-shaped area within 10 to 20 km from the headquarter, …, and to Zone 5 covering the circular ring-shaped area within 40 to 50 km from the headquarter. BDE is calculated as the weighted sum of the number of bird species within each zone using a linear weighting scheme starting with 0.25 for Zone 1 and decrease by 0.025 each time for the following zones (i.e., 0.225 for Zone 2, …, and 0.15 for Zone 5). The figures in the upper right box denote the number of bird species within each zone for the sample firm.

Figure 2. Time trend of BDE

This figure depicts the time series of the quarterly median of firm-level BDEs over the full sample period. Firm-level *BDE* is calculated the distance-weighted richness in bird species within a 50-kilometer radius surrounding the firm location. The black and blue dashed lines are the pre- and post-GSA average of median BDE, respectively. The vertical line represents the launch of GSA in 2017Q3.

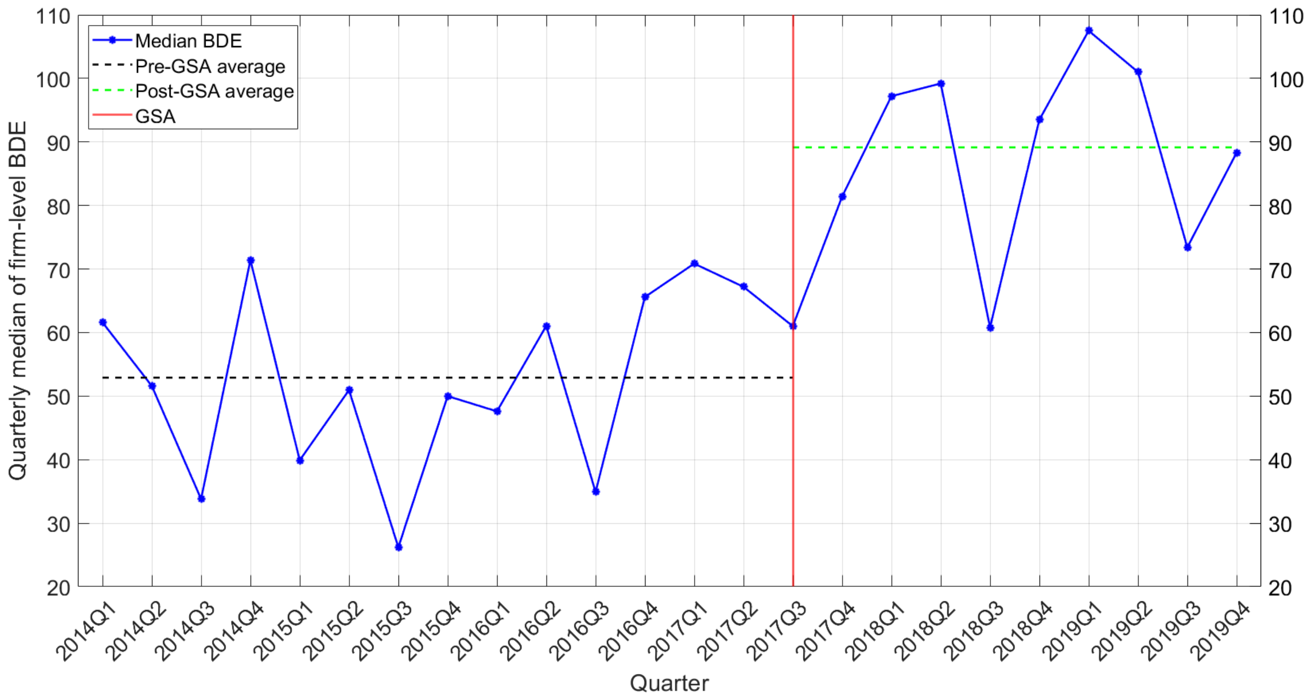

Figure 3. Time trend of bond spreads by BDE

The figure illustrates the time trend of bond spreads by BDE. It plots the slope coefficients from the rolling regression of bond spreads on pre-GSA BDE, controlling for firm and city fixed effects. Standard errors are clustered at the firm level. The rolling regression is performed separately for low-BDE and high-BDE firms. The vertical line indicates the launch of the GSA in 2017Q3.

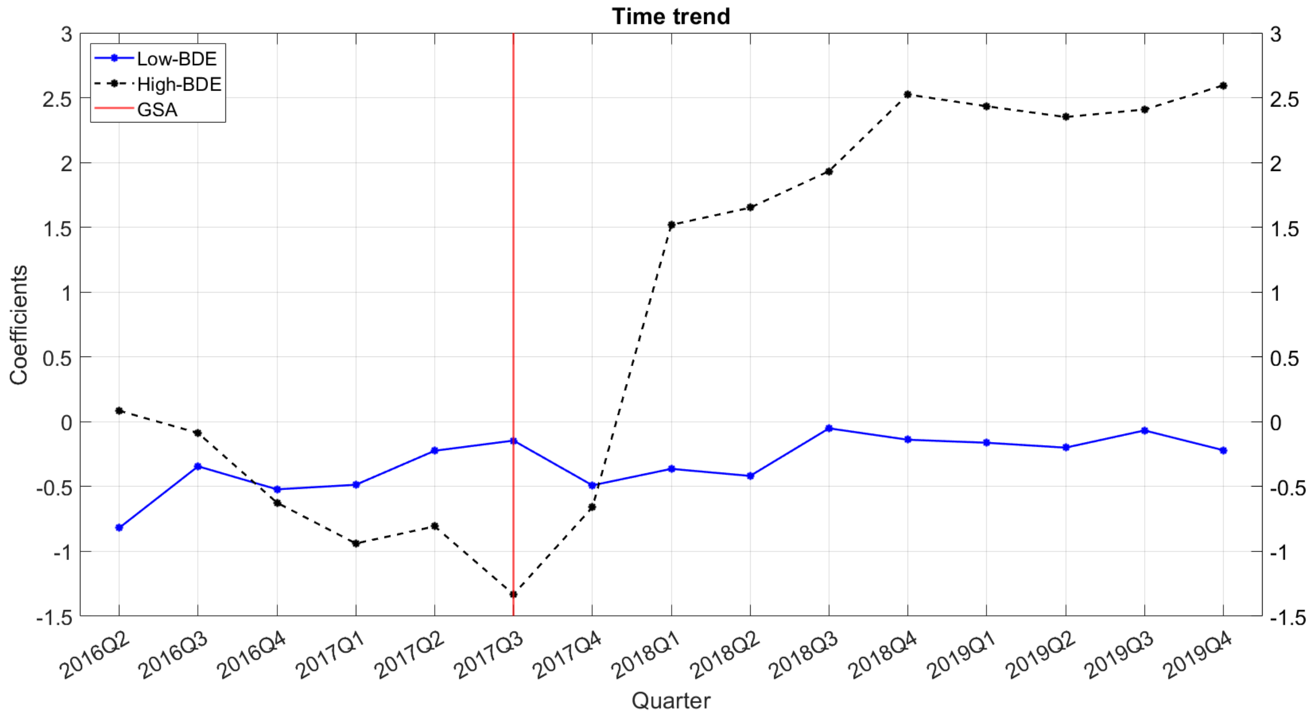

Table 1: Summary statistics

Panel A of the table reports the summary statistics of bond and issuer features in the secondary market, while Panel B reports the bond contracting terms in the primary market. *BDE* is the distance-weighted richness in bird species within a 50-kilometer radius surrounding the firm location. *HighBDE* is a dummy variable, which equals one if a firm's pre-treatment BDE (averaged over quarters from 2014Q1 to 2016Q4) exceeds the median *BDE* of all firms, and zero otherwise. *Spread* is the difference between a bond's yield and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points). *Time-to-maturity* is the residual maturity of a bond, capturing the time difference between the trading date and its maturity date (in years). *At-issue-maturity* is a bond's at-issue maturity (in years). *Bondsize* is the logarithm of a bond's issuing amount. *Rating* is a numerical value converted from the letter grade of bond ratings, starting from 1 for AAA, 2 for AA+, through 8 for ratings below A. *Callable* is a dummy variable that equals one for bonds issued with callable options, and zero otherwise. *Puttable* is a dummy variable that equals one for bonds issued with puttable options, and zero otherwise. *Size* is the logarithm of the issuer's total assets. *Leverage* is the issuer's total liabilities divided by total assets. *ROA* is the issuer's return on assets (in percentage points). For bond contracting terms in the primary market, each bond issuance is counted as one observation. *Issue_amount* is the offering amount of a bond (in billion yuan RMB). *At-issue-maturity* is a bond's maturity at-issue (in years). *Spread_primary* is the difference between a bond's coupon rate and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points).

	(1) N	(2) Mean	(3) SD	(4) P25	(5) P50	(6) P75
Panel A: Bond and issuer characteristics in the secondary market						
BDE	10,171	76.647	75.511	7.383	53.95	149.275
HighBDE	10,171	0.556	0.497	0	1	1
Spread (%)	10,171	1.231	1.348	0.353	0.939	1.799
Time-to-maturity (yr)	10,171	3.303	1.671	2.083	2.987	4.161
At-issue-maturity (yr)	10,171	5.669	1.996	5	5	7
Bondsize (log)	10,171	2.351	0.841	1.792	2.303	2.996
Rating	10,171	1.936	0.875	1	2	3
Callable	10,171	0.079	0.270	0	0	0
Puttable	10,171	0.688	0.463	0	1	1
Size (log)	10,171	24.312	1.603	23.122	24.029	25.385
Leverage	10,171	0.591	0.155	0.479	0.596	0.715
ROA (%)	10,171	3.136	3.620	1.396	2.782	4.692
Panel B: Bond contracting terms in the primary market						
Issue_amount (billion yuan)	905	1.263	1.288	0.5	1	1.5
At-issue-maturity (yr)	905	4.423	1.381	3	5	5
Spread_primary (%)	905	1.564	1.214	0.654	1.187	2.394

Table 2: Summary statistics before and after GSA

This table reports the summary statistics for bond subsamples in Phase 1 and Phase 2, respectively. Phase 1 is the pre-GSA period spanning from 2014Q1 to 2017Q2, and Phase 2 is the post-GSA period spanning from 2017Q3 to 2019Q4. Bond and issuer characteristics are defined the same as in **Table 1**.

	(1)	(2)	(3)	(4)	(5)	(6)
		Phase 1			Phase 2	
	N	Mean	SD	N	Mean	SD
Spread	5,491	1.297	1.412	4,680	1.188	1.644
Time-to-maturity	5,491	3.545	1.786	4,680	3.019	1.475
At-issue-maturity	5,491	5.931	1.947	4,680	5.360	2.009
Bondsize	5,491	2.308	0.840	4,680	2.401	0.840
Rating	5,491	2.128	0.865	4,680	1.710	0.832
Callable	5,491	0.043	0.202	4,680	0.121	0.326
Puttable	5,491	0.701	0.458	4,680	0.672	0.470
ROA	5,491	2.913	3.980	4,680	3.396	3.126
Size	5,491	23.888	1.548	4,680	24.808	1.538
Leverage	5,491	0.578	0.162	4,680	0.606	0.152
Issue_amount	423	1.340	1.549	482	1.195	1.003
At-issue-maturity	423	4.792	1.395	482	4.100	1.286
Spread_primary	423	1.520	1.299	482	1.603	1.134

Table 3: BDE and bond spreads

This table reports the impact of corporate biodiversity endowment on bond spreads before and after GSA. The dependent variable, *Spread*, is the difference between a bond's yield and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points). *HighBDE* is a dummy variable, which equals one if a firm's pre-treatment BDE (averaged over quarters from 2014Q1 to 2016Q4) exceeds the median *BDE* of all unique firms, and zero otherwise. *Post* is a dummy variable that equals one for the time period after the launch of GSA (2017Q3), and zero otherwise. All other bond and issuer characteristics are defined the same as in **Table 1**. Standard errors in parentheses are clustered at the firm level. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	Spread		
	(1)	(2)	(3)
Post×HighBDE	0.674***	0.666***	0.663***
	(0.238)	(0.229)	(0.208)
Bondsize		-0.028	-0.025
		(0.057)	(0.057)
Rating		0.258	0.273*
		(0.170)	(0.160)
Time-to-maturity		0.086***	0.082***
		(0.022)	(0.021)
At-issue-maturity		-0.006	-0.003
		(0.019)	(0.018)
Callable		0.231	0.255
		(0.161)	(0.159)
Puttable		-0.269***	-0.274***
		(0.103)	(0.101)
Size			-0.361**
			(0.182)
Leverage			0.914
			(0.767)
ROA			-0.047***
			(0.013)
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.793	0.799	0.802
Observations	10,171	10,171	10,171

Table 4: BDE and industry-adjusted spread

The table reports the impact of corporate biodiversity endowment on adjusted bond spreads before and after GSA. The dependent variable, *Adjusted Spread*, is the industry-adjusted spread calculated as the difference between a bond's yield spread in quarter t and the median spread of the issuer's industry in quarter t (in percentage points). *HighBDE* is a dummy variable, which equals one if a firm's pre-treatment BDE (averaged over quarters from 2014Q1 to 2016Q4) exceeds the median *BDE* of all unique firms, and zero otherwise. *Post* is a dummy variable that equals one for the time period after the launch of GSA, and zero otherwise. All other bond and issuer characteristics are defined the same as in **Table 1**. Standard errors in parentheses are clustered at the firm level. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	Adjusted Spread		
	(1)	(2)	(3)
Post×HighBDE	0.593**	0.596**	0.590**
	(0.270)	(0.258)	(0.244)
Bondsize		-0.025	-0.022
		(0.056)	(0.056)
Rating		0.300*	0.310*
		(0.168)	(0.162)
Time-to-maturity		0.086***	0.083***
		(0.022)	(0.022)
At-issue-maturity		-0.007	-0.005
		(0.019)	(0.019)
Callable		0.223	0.236
		(0.162)	(0.162)
Puttable		-0.262**	-0.266***
		(0.102)	(0.101)
Size			-0.210
			(0.151)
Leverage			0.292
			(0.498)
ROA			-0.035***
			(0.013)
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.766	0.773	0.774
Observations	10,171	10,171	10,171

Table 5: BDE and bond contracting terms

This table reports the impact of corporate biodiversity endowment on bond contracting terms in the primary market. The dependent variables in columns (1), (2), and (3) are *Scaled_bondsize*, defined as the offering amount of a bond scaled by the total assets of the issuer (in percentage points), *Spread_primary*, defined as the difference between the coupon rate of a bond and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points), and *At-issue-maturity,* defined as a bond's at-issue-maturity (in years), respectively. *HighBDE* is a dummy variable, which equals one if a firm's pre-treatment BDE (averaged over quarters from 2014Q1 to 2016Q4) exceeds the median *BDE* of all unique firms, and zero otherwise. *Post* is a dummy variable that equals one for the time period after the launch of GSA, and zero otherwise. Standard errors in parentheses are clustered at the firm level. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	Scaled_bondsize	Spread_primary	At-issue-maturity
	(1)	(2)	(3)
Post×HighBDE	-3.293***	0.829	-2.178
	(0.882)	(0.776)	(1.700)
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.970	0.971	0.753
Observations	905	905	905

Table 6: BDE and real economic activities

The table reports the estimated heterogeneous effects of BDE on real economic activities before and after GSA. The dependent variable in column (1), *Nightlight intensity*, is the quarterly average nighttime luminosity within a 5-kilometer radius surrounding a firm. The dependent variable in Column (2), *Production-related TIR* (thermal infrared radiation), is calculated by subtracting natural TIR from observed TIR within a 5-kilometer radius around a firm. *HighBDE* is a dummy variable, which equals one if a firm's pre-treatment BDE (averaged over quarters from 2014Q1 to 2016Q4) exceeds the median *BDE* of all unique firms, and zero otherwise. *Post* is a dummy variable that equals one for the time period after the launch of GSA, and zero otherwise. Standard errors in parentheses are clustered at the firm level. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	Nightlight intensity	Production-related TIR
	(1)	(2)
Post×HighBDE	-4.114**	-2.844***
	(2.077)	(0.655)
Controls	YES	YES
Firm FEs	YES	YES
City×Quarter FEs	YES	YES
R^2	0.926	0.825
Observations	12,480	9,237

Table 7: BDE and fundamental performance

This table reports the estimated heterogeneous effects of BDE on firm fundamental performance after GSA. The dependent variable in panel A (B), $\Delta ROA_{i,t+\tau}$ ($\Delta ROE_{i,t+\tau}$), is the post-GSA change in quarterly ROA (ROE) averaged over τ quarters after GSA (i.e.,τ =1 for 2017Q4 and τ =9 for 2019Q4). *HighBDE* is a dummy variable, which equals one if a firm's pre-treatment BDE (averaged over quarters from 2014Q1 to 2016Q4) exceeds the median *BDE* of all unique firms, and zero otherwise. Size is the lagged total assets of the bond issuer. Standard errors clustered at the firm level are in parentheses. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: BDE and post-GSA ROA change

	$\Delta ROA_{i,t+\tau}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	τ =1	$\tau \in$[1,2]	$\tau \in$[1,3]	$\tau \in$[1,4]	$\tau \in$[1,5]	$\tau \in$[1,6]	$\tau \in$[1,7]	$\tau \in$[1,8]	$\tau \in$[1,9]
HighBDE	-1.185***	-1.279***	-1.333***	-1.375***	-1.444***	-1.478***	-1.499***	-1.501***	-1.472***
	(0.332)	(0.335)	(0.340)	(0.342)	(0.345)	(0.352)	(0.359)	(0.365)	(0.360)
Size	0.227*	0.258**	0.275**	0.287**	0.330**	0.347***	0.360***	0.372***	0.395***
	(0.118)	(0.121)	(0.125)	(0.128)	(0.131)	(0.134)	(0.137)	(0.139)	(0.135)
Quarter FEs	-	YES	YES	YES	YES	YES	YES	YES	YES
Industry FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.086	0.090	0.093	0.094	0.091	0.085	0.084	0.084	0.080
Observations	521	1,040	1,558	2,078	2,601	3,123	3,647	4,170	4,694

Panel B: BDE and post-GSA ROE change									
	$\Delta ROE_{i,t+\tau}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\tau=1$	$\tau\in[1,2]$	$\tau\in[1,3]$	$\tau\in[1,4]$	$\tau\in[1,5]$	$\tau\in[1,6]$	$\tau\in[1,7]$	$\tau\in[1,8]$	$\tau\in[1,9]$
HighBDE	-2.848***	-3.020***	-3.075***	-3.161***	-3.364***	-3.493***	-3.537***	-3.536***	-3.413***
	(0.896)	(0.885)	(0.887)	(0.890)	(0.880)	(0.888)	(0.903)	(0.916)	(0.894)
Size	0.394	0.462	0.568	0.623	0.718*	0.764**	0.807**	0.837**	0.853**
	(0.379)	(0.382)	(0.380)	(0.382)	(0.380)	(0.383)	(0.388)	(0.393)	(0.380)
Quarter FEs	-	YES	YES	YES	YES	YES	YES	YES	YES
Industry FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.070	0.072	0.073	0.073	0.077	0.077	0.077	0.078	0.076
Observations	520	1,038	1,554	2,072	2,595	3,117	3,641	4,164	4,695

Table 8: BDE, spreads, and regulation intensity

This table reports the estimated heterogeneous effects of BDE on bond spreads under different levels of regulatory intensity. The dependent variable, *Spread*, is the difference between a bond's yield and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points). *HighBDE* is a dummy variable, which equals one if a firm's pre-treatment BDE (averaged over quarters from 2014Q1 to 2016Q4) exceeds the median *BDE* of all unique firms, and zero otherwise. *Post* is a dummy variable that equals one for the time period after the launch of GSA, and zero otherwise. Tightness is a dummy variable that equals one if the total number of local officials held accountable in GSA-related environmental inspections within a province scaled by its provincial GDP is above the sample median of all unique provinces, and zero otherwise. Standard errors in parentheses are clustered at the firm level. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	Spread		
	(1)	(2)	(3)
Post×HighBDE×Tightness	0.754**	0.689*	0.613*
	(0.369)	(0.383)	(0.319)
Post×HighBDE	0.360	0.380	0.408
	(0.318)	(0.287)	(0.274)
Other triple difference terms	YES	YES	YES
Bond controls	NO	NO	YES
Firm controls	NO	YES	YES
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.793	0.799	0.802
Observations	10,171	10,171	10,171

Table 9: BDE, spreads, and the Paris Agreement

This table reports the heterogenous impact of BDE on bond spreads before and after the Paris Agreement in 2015Q4. The sample period spans from 2014Q1 to 2017Q2. The dependent variable, *Spread*, is the difference between a bond's yield and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points). *HighBDE* is a dummy variable, which equals one if a firm's pre-treatment BDE, averaged over quarters in 2014, exceeds the median *BDE* of all unique firms, and zero otherwise. *Post2015Q4* is a dummy variable that equals one for the time period after the Paris agreement (i.e., from 2015Q4 onwards), and zero otherwise. Standard errors in parentheses are clustered at the firm level. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	Spread		
	(1)	(2)	(3)
Post2015Q4×HighBDE	0.016	-0.091	-0.054
	(0.340)	(0.372)	(0.337)
Bond controls	NO	NO	YES
Firm controls	NO	YES	YES
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.850	0.856	0.858
Observations	5,193	5,193	5,193

Table 10: BDE, spreads, and ESG performance

This table examines the relationship between BDE, spreads and firms' ESG performance. The dependent variable, *Spread*, is the difference between a bond's yield and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points). *HighBDE* is a dummy variable, which equals one if a firm's pre-treatment BDE (averaged over quarters from 2014Q1 to 2016Q4) exceeds the median *BDE* of all unique firms, and zero otherwise. *Post* is a dummy variable that equals one for the time period after the launch of GSA, and zero otherwise. *High_ESG* (*High_E*) is a dummy variable that equals one if a firm's annual ESG (E) score averaged over 2014 to 2016 is higher than the sample median of unique firms over the same period, and zero otherwise. Standard errors in parentheses are clustered at the firm level. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	Spread	
	(1)	(2)
Post×HighBDE×High_ESG	-0.033	
	(0.408)	
Post×HighBDE×High_E		-0.387
		(0.314)
Post×High_ESG	-0.242	
	(0.333)	
Post×High_E		0.066
		(0.235)
Post×HighBDE	0.753**	0.770***
	(0.361)	(0.216)
Bond controls	YES	YES
Firm controls	YES	YES
Firm FEs	YES	YES
City×Quarter FEs	YES	YES
R^2	0.782	0.783
Observations	8,263	8,263

Appendix

Part A: A Structural Credit Risk Framework

We employ a structural credit model to rationalize the yield spread changes on high-BDE issuers following the implementation of GSA.

The Merton (1974) Model

Following Merton (1974) and He and Xiong (2012), a firm's asset value V_t follows a geometric Brownian motion under the risk-neutral measure:

$$dV_t = (r - \delta)V_t dt + \sigma V_t dW_t,$$

where r is the risk-free interest rate, δ is the payout ratio, and σ is the volatility of the asset value. The firm's equity is modeled as a call option on the asset value with strike price equal to the face value of debt D and time to maturity T. The equity payoff at maturity is:

$$S_T = \max(V_T - D, 0).$$

Biological Diversity Endowment, Regulatory Cost, and the GSA Impact

We measure a firm's Biological Diversity Endowment (BDE) as the summation of the number of wildlife species (scaled by their ecological contribution):

$$\sum_{g=1}^{G} S_g^{\phi_g},$$

where S_g is the number of species in the g-th functional group, and $\phi_g < 1$ captures the nonlinear ecological contribution of species (Giglio et al., 2024). The ecological contribution (i.e., ecosystem services) includes, but not limited to, pollination, nutrient recycling, water purification, and pest control.

Consistent with our key identification assumption in the maintext that a firm's biological diversity endowment is positively correlated with its regulatory and compliance cost, we set the regulatory cost on the firm as a scaling function of its BDE:

$$R = \kappa_B \sum_{g=1}^{G} S_g^{\phi_g},$$

where $\kappa_B > 0$ denotes the unit cost imposed by regulatory tightness.

The implementation of GSA, aimed at biodiversity conservation, enlarges the regulatory cost on high-BDE firms through more restrictions on land use, resource access, and operations, because they are located within a high-stakes natural environment and subject to more regulatory scrutiny by the regulators.

Note the regulatory cost R reduces the terminal asset value to $V_T - R$, or equivalently, it increases the effective strike price to $D + R$. Additionally, the implementation of GSA lowers the initial asset value to $V_{0'} < V_0$ and increases volatility to $\sigma' > \sigma$ due to regulatory uncertainty.

Estimating the Credit Spread and Distance to Default

In the Merton model, the equity value is:

$$E = V_0 e^{-\delta T}\Phi(d_1) - De^{-rT}\Phi(d_2),$$

where:

$$d_1 = \frac{\ln(V_0/D) + (r - \delta + \sigma^2/2)T}{\sigma\sqrt{T}},$$

$$d_2 = d_1 - \sigma\sqrt{T},$$

and Φ is the standard normal cumulative distribution function.

The value of a risky zero-coupon bond is the risk-free bond value minus a put option on the firm's assets with strike price D:

$$P = e^{-rT}\left[D\Phi(d_2) + V_0 e^{-\delta T}\Phi(-d_1)\right].$$

The credit spread (CS) of a zero-coupon bond reflects the additional yield required to compensate for default risk, defined as the difference between the bond's yield y and the risk-free rate r. The yield is derived from the bond price:

$$y = -\frac{1}{T}\ln\left(\frac{P}{D}\right),$$

so the credit spread is:

$$CS = -\frac{1}{T}\ln\left(\frac{P}{D}\right) - r.$$

The risk-neutral probability of default is $\Phi(-d_2)$, the likelihood that $V_T < D$. The distance to default (DD) measures how far the firm's asset value is from the default threshold in standard deviations:

$$\mathrm{DD} = \frac{\ln(V_0/D) + (r - \delta - \sigma^2/2)T}{\sigma\sqrt{T}}.$$

After the implementation of GSA, with updated parameters $V_{0'}$, σ', and effective strike price $D + R$, the equity value of high-BDE firms becomes:

$$E_{\text{post-GSA}} = V_{0'} e^{-\delta T} \Phi(d_{1'}) - (D + R) e^{-rT} \Phi(d_{2'}),$$

where:

$$d_{1'} = \frac{\ln(V_{0'}/(D + R)) + (r - \delta + (\sigma')^2/2)T}{\sigma' \sqrt{T}},$$

$$d_{2'} = d_{1'} - \sigma' \sqrt{T}.$$

Considering the GSA, we adjust d_1 and d_2 to $d_{1'}$ and $d_{2'}$. The bond price post-GSA is:

$$P_{\text{post-GSA}} = e^{-rT} \left[D\Phi(d_{2'}) + V_{0'} e^{-\delta T} \Phi(-d_{1'}) - R\Phi(d_{2'}) \right].$$

The credit spread post-GSA is:

$$CS_{\text{post-GSA}} = -\frac{1}{T} \ln \left(\frac{P_{\text{post-GSA}}}{D} \right) - r.$$

The distance to default post-GSA is:

$$\text{DD}_{\text{post-GSA}} = \frac{\ln(V_{0'}/(D + R)) + (r - \delta - (\sigma')^2/2)T}{\sigma' \sqrt{T}}.$$

Proposition 1: High-BDE firms experience a significant increase in credit spreads (and a decrease in distance to default) after the GSA.

Overall, the structural credit model illustrates that biodiversity transition risk is incorporated into the bond market. After the implementation of GSA, high-BDE firms exhibit higher credit spreads and lower distances to default compared to low-BDE firms.

Table A.1: Variables descriptions

This table lists the variable definitions and data sources used.

Variable	Description	Source
Panel A: Bond and issuer features in the secondary market		
Spread	The difference between a bond's yield and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points). A bond's yield is based on the last transaction taking place on the last active trading day of the quarter. This variable is winsorized at the 1st and 99th percentiles.	CSMAR
BDE	A biological diversity endowment measure that quantifies bird diversity within a 50-kilometer radius surrounding a firm's headquarter. To construct this measure, we first collect data on the number of bird species at intervals of every 10 kilometers from eBird. These data are then weighted based on their proximity to the corporate headquarters, with the normalized weights decreasing linearly, starting from 0.25 within the first 10 kilometers to 0.15 for distances between 40 and 50 kilometers. The weighted observations are subsequently aggregated to form the BDE measure.	Data on bird species and location: eBird Data on firm location: CSMAR
Rating	A numerical value converted from its letter grade: 1 for AAA, 2 for AA+, through 8 for ratings below A.	CSMAR, RESSET
Bondsize	The logarithm of a bond's issuing amount, in yuan RMB.	CSMAR, RESSET
Time-to-maturity	The time difference between a bond's trading date and its fixed maturity date, in years.	CSMAR, RESSET
At-issue-maturity	A bond's maturity at-issue (in years).	CSMAR, RESSET
Puttable	A dummy variable that equals one for bonds issued with puttable options, and zero otherwise.	CSMAR, RESSET
Callable	A dummy variable that equals one for bonds issued with callable options, and zero	CSMAR, RESSET

	otherwise.	
ROA	The issuer's return on assets (in percentage points).	CSMAR
Size	The logarithm of the issuer's total assets, in yuan RMB	CSMAR
Leverage	The issuer's total liabilities divided by total assets.	CSMAR
Panel B: Bond contracting terms in the primary market		
Issue_amount	The actual offering amount of a bond (in billion yuan RMB).	RESSET, CSMAR
At-issue-maturity	A bond's maturity at-issue (in years).	RESSET
Spread_primary	The difference between a bond's coupon rate and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points).	RESSET

Table A.2: Sample construction of the secondary market bonds

The table details the steps and filtering rules used to construct the quarterly sample of bond spreads and other bond and issuer characteristics.

Sample construction process	Number of Obs.
Full bond secondary market sample from CSMAR	1,683,830
Not publicly listed	-1,053,738
Keep data for the last transaction in each quarter	-615,272
Lack information	-452
Hand collected	452
RESSET data	75
Finance industry	-824
st,*st	-952
Delist	-284
Default	-226
Lack significant information due to unlisted	-170
Residual maturity<=1 year	-2,268
Final sample	**10,171**

Table A.3: Robustness checks

This table reports the impact of corporate biodiversity endowment on bond spreads before and after GSA under a battery of robustness checks. Panel A uses bond fixed effects in lieu of firm fixed effects. Panel B adopts the two-way clustered standard errors (at the firm and quarter levels). Panel C uses weighted least square (WLS) method, weighted by bond sized. Panel D examines alternative subsamples by excluding firms headquartered in Beijing, Shanghai, and Guangdong provinces: Column (1) excludes Beijing firms only, Column (2) excludes Beijing and Shanghai firms, and Column (3) excludes Beijing, Shanghai, and Guangdong firms. Panel E examines the subsample limited to manufacturing firms only. Panel F reports the propensity score analysis of difference-in-differences estimates: In Column (1), the treatment firms are matched with firms in the control group based on propensity scores estimated (in the first stage logit model). In Columns (2) and (3), two distinct methods are utilized to balance covariates based on the propensity scores derived from the first stage, following the approach outlined by Bonsall (2014). The method in Column (3) incorporates the propensity score and an interaction term between the propensity score and the difference-in-differences interaction as additional regressors in the regression model. The dependent variable, *Spread*, is the difference between a bond's yield and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points). *HighBDE* is a dummy variable, which equals one if a firm's pre-treatment BDE (averaged over quarters from 2014Q1 to 2016Q4) exceeds the median *BDE* of all unique firms, and zero otherwise. *Post* is a dummy variable that equals one for the time period after the launch of GSA (2017Q3), and zero otherwise. All other bond and issuer characteristics are defined the same as in **Table 1**. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Bond fixed effects		
	(1)	(2)	(3)
Post×HighBDE	0.497**	0.486**	0.490**
	(0.247)	(0.243)	(0.207)
Bond controls	NO	YES	YES
Firm controls	NO	NO	YES
Bond FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.850	0.850	0.852
Observations	10,171	10,171	10,171

	Panel B: Two-way clustered standard errors		
	(1)	(2)	(3)
Post×HighBDE	0.674**	0.666**	0.663**
	(0.293)	(0.296)	(0.270)
Bond controls	NO	YES	YES
Firm controls	NO	NO	YES
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.793	0.799	0.802
Observations	10,171	10,171	10,171

	Panel C: Weighted least square (WLS) estimates		
	(1)	(2)	(3)
Post×HighBDE	0.795***	0.760***	0.757***
	(0.264)	(0.245)	(0.230)
Bond controls	NO	YES	YES
Firm controls	NO	NO	YES
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.783	0.790	0.793
Observations	10,109	10,109	10,109

	Panel D: Excluding Beijing, Shanghai, and Guangdong firms		
	(1)	(2)	(3)
Post×HighBDE	0.668***	0.674***	0.526**
	(0.207)	(0.218)	(0.252)
Bond controls	YES	YES	YES
Firm controls	YES	YES	YES
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.821	0.826	0.847
Observations	8,100	7,244	5,625

	Panel E: Manufacturing firms only		
	(1)	(2)	(3)
Post×HighBDE	1.114***	1.208***	1.102***
	(0.216)	(0.410)	(0.316)
Bond controls	NO	YES	YES
Firm controls	NO	NO	YES
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.853	0.857	0.861
Observations	4,165	4,165	4,165

	Panel F: PSM-DID estimates		
	(1)	(2)	(3)
Post×HighBDE	0.825***	0.687***	1.175***
	(0.297)	(0.243)	(0.304)
Additional regressors	NO	NO	YES
Bond controls	YES	YES	YES
Firm controls	YES	YES	YES
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.820	0.800	0.804
Observations	7,966	10,171	10,171

Table A.4: BDE and distance to default (DD)

This table reports the impact of corporate biodiversity endowment on the distance to default before and after GSA. The dependent variable is the Merton distance to default (DD) in Bharath and Shumway (2008). HighBDE is a dummy variable, which equals one if a firm's pre-treatment BDE (averaged over quarters from 2014Q1 to 2016Q4) exceeds the median BDE of all unique firms, and zero otherwise. Post is a dummy variable that equals one for the time period after the launch of GSA (2017Q3), and zero otherwise. All other bond and issuer characteristics are defined the same as in Table 1. Standard errors in parentheses are clustered at the firm level. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	Distance to default (DD)		
	(1)	(2)	(3)
Post×HighBDE	-2.396***	-2.181***	-2.086***
	(0.687)	(0.632)	(0.632)
Bond controls	NO	YES	YES
Firm controls	NO	NO	YES
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.646	0.650	0.654
Observations	9,931	9,931	9,931

Table A.5: Falsification test with industry-level BDE

This table performs the falsification test by using the industry-level BDE in lieu of the firm-level BDE to examine the impact of corporate biodiversity endowment on bond spreads before and after GSA. The dependent variable, *Spread*, is the difference between a bond's yield and Chinese Development Bank bonds' yield on the same day with the same maturity (in percentage points). $HighBDE^{Ind}$ is a dummy variable that equals one if a firm's industry-level BDE is above the median BDE across all industries. *Post* is a dummy variable that equals one for the time period after the launch of GSA (2017Q3), and zero otherwise. All other bond and issuer characteristics are defined the same as in Table 1. Standard errors in parentheses are clustered at the firm level. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	Spread		
	(1)	(2)	(3)
Post×HighBDE^{Ind}	0.025	0.096	0.129
	(0.135)	(0.126)	(0.134)
Bond controls	NO	YES	YES
Firm controls	NO	NO	YES
Firm FEs	YES	YES	YES
City×Quarter FEs	YES	YES	YES
R^2	0.793	0.799	0.802
Observations	10,171	10,171	10,171