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The Impact of Biodiversity Risk on Banks' Credit Default Swap Spread Changes

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Abstract

This paper explores the impact of biodiversity risk on banks' credit risk using a news- based biodiversity index and CDS of 39 global banks between 2015 and 2023. Using a linear OLS regression, this paper finds evidence for a significant positive relationship between biodiversity news and CDS spread changes, where negative news leads to increasing CDS prices. Furthermore, cross-sectional analyses are conducted to test for heterogeneity. Using the Kunming Declaration in 2021 as an external shock, this paper finds evidence that the relationship persists for the period after the Kunming Declaration, suggesting no significant effect of biodiversity risk before. Further tests reveal no significant impact of a country's state of biodiversity. In contrast, since the Kunming Declaration, the relationship is stronger for banks which openly disclose biodiversity risks. Banks located in the USA, the only UN nation which is not a member of the CBD, experience a weaker effect of biodiversity news on CDS spread changes. These results show that banks are subject to biodiversity-related credit risks, where expectations of new policies and regulation following the Kunming Declaration significantly affect banks' CDS spreads.

Keywords: biodiversity; banking; credit default swaps; credit risk

1 Introduction

"We are all asset managers."

- Partha Dasgupta (2021, p. 35)

One of the most important assets accessible to humanity is nature, with all its living and non-living components (IPBES, 2019). In addition to being the foundation of life, nature also plays a key role in the way humans interact with each other and its surroundings. Humanity has learned to use nature and its assets for its benefit, forming economies like agriculture, medicine, or construction (WEF, 2020). Such industries strongly rely on the variety of ecosystems, or in other words, life and its diversity – biodiversity. A study by the World Economic Forum (WEF) has underlined this reliance, finding that more than 50% of the world's value creation is dependent on nature-related services (WEF, 2020). But global ecosystems and their diversity are fading. Among plants and land-based animals, it is estimated that about 20% of species could be extinct in the next decades alone (Dasgupta, 2021). Consequently, this area of risk has experienced increasing attention in recent years.

In 2019, IPBES published the global assessment report on biodiversity and ecosystem services, which aims to provide policymakers and private sectors with credible information about the current state of biodiversity (IPBES, 2019). Importantly, they discuss the interaction between humanity and its environment to highlight its effects on nature's deterioration. They state that due to human action, 75% of the global land surface has been altered, 85% of wetland areas have been lost, and global forest area is heavily declining. Furthermore, the rate of species extinction is 10 to 100 times larger than on average over the past 10 million years. Key drivers of these developments, like land- and sea-use change or climate change, are caused by human interactions with the environment.

The WEF (2020) report on nature lays out the dependence of global economies on biodiversity and examines the outcomes of its loss. The risks associated with biodiversity degradation can directly or indirectly appear through different channels, all with the potential to destabilize businesses and markets. However, assessing which industries are most likely affected is not always evident. The report states that in many industries, seemingly only a small portion of value creation is highly dependent on ecosystem services. However, there exist hidden dependencies, where large parts of the gross value added are at least moderately reliant on nature. For secondary and tertiary industries, nature-related risks can be significant through supply chains, even though they don't seem to be highly dependent at first glance. The report adds that the gravity of potential losses can be shown, despite these difficulties. The food and beverages, as well as construction and agriculture industries, are highly reliant on nature services. Together they generate about 8 trillion dollars of gross value added, which could significantly decrease, as these industries suffer from nature loss.

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Given the potential severity of economic consequences, there have been approaches to motivate global solutions. In 1993, the Convention on Biological Diversity (CBD) was launched with the goal to drive biodiversity conservation and ensure fair and sustainable use of resources (CBD Secretariat, 2011). With its nearly 200 member states, coordinated steps are decided and biodiversity targets are formulated. Recently, the particularly important Kunming Declaration in 2021 has received global attention and is viewed as the biodiversity equivalent to the climate-focused Paris Agreement (Garel et al., 2024). The CBD Secretariat (2021a) has even declared it to be the "most important United Nations Biodiversity event of this decade" (p. 6). In the context of the declaration, the CBD Secretariat (2021a) has also stressed the significant role of the financial sector in working towards positive biodiversity outcomes and discussed potential risks. While financial firms can provide capital to drive the conservation of biodiversity, they also need to acknowledge how biodiversity risks can negatively affect their business. As stated by Dasgupta (2021), the "loss of biodiversity [...] results in greater volatility and uncertainty around the goods and services ecosystems provide" (p. 417). These increased risks especially influence banks' operations and credit business, which may be affected by either transition risks through new regulation, or physical risks, like the loss of species or ecosystems their clients depend on (CBD Secretariat, 2021a).

While the threat of biodiversity loss is well established, the effects on the financial sector are just starting to be studied (Calice et al., 2023). Karolyi and Tobin-de la Puente (2023) acknowledge the lack of biodiversity-related finance literature and call for research. Within the finance industry, banks assume a special role due to their business models, asset-liability structures, and regulatory requirements. Consequently, research often excludes them from empirical credit risk investigations (Hasan et al., 2016). However, banks' risks are significantly exposed to biodiversity concerns through several channels, according to Hudson (2024). He explains that biodiversity loss could disrupt supply chains and harm the operating business of banks' clients, causing potential default on loan obligations. Furthermore, the value of security portfolios may decline as economies struggle with the consequences of biodiversity loss, which potentially leads to downgrades of a bank's creditworthiness. Regulatory issues, resulting in legal or reputational repercussions, or the loss of potential investment opportunities due to biodiversity concerns, add to the risks banks face (Hudson, 2024). This thesis aims to answer the call for research by Karolyi and Tobin-de la Puente and investigates whether biodiversity risks significantly influence banks' credit risk.

To examine this relation, a sample of 39 global banks is constructed for the time between 2015 and 2023. As a measure of biodiversity risk, this thesis uses a novel approach published by Giglio et al. (2023). They construct a news-based measure by analyzing New York Times articles for specific keywords related to biodiversity. Relevant reports are classified regarding their sentiment to aggregate positive and negative news. This creates a high-frequency biodiversity index, which provides daily data observations. As a measure for credit risk, credit default swaps (CDS) are used. These derivatives act as insurance in case of credit events and therefore provide a measure of credit default risk of the underlying entity (Zhu, 2006). In addition, control variables are used, which have shown to be significant determinants of CDS prices in credit derivative literature. One set of controls are balance sheet variables, including leverage ratio, asset quality, bank size, funding stability, cost efficiency, and sensitivity to market risk. Additional non-balance sheet variables include a bank's stock volatility as well as returns and volatility of stock indices. Lastly, sovereign bond yields and credit ratings are included in the analysis.

The analysis employs a linear panel ordinary least squares (OLS) estimation with fixed effects and clustered standard errors. The baseline regression provides evidence for a significant positive relationship between biodiversity news and CDS spread changes. The economic magnitude of the effect is in the range of a 1.532% to 1.563% increase in CDS price changes for every standard deviation increase of the biodiversity index. Beside biodiversity, the equity variables are all significantly affecting CDS price changes as well. Balance sheet variables do not have a significant impact, which persists when introducing a time lag of one period. To test for heterogeneity of this relationship, further analyses introduce cross-sectional interaction terms. Motivated by its significance and public attention, this thesis studies the effect of the Kunming Declaration as an external shock. For the full sample, the analysis only shows evidence for a significant positive effect in the post-Kunming period and not before. These results are in line with the findings of Garel et al. (2024), who find similar biodiversity risk effects in stock markets only after the declaration. Introducing a country's state of biodiversity does not show any diverging effects compared to the baseline regression. For the banks in the sample, the country's biodiversity degradation therefore does not seem to influence the magnitude of the relation. Kölbel et al. (2022) and Carbone et al. (2021) show that the disclosure and acknowledgement of climate-related risk has been shown to have impacts on firm's credit risk. Similarly, this thesis includes the participation of banks in responsible banking initiatives as so-called green banks to test for heterogeneity. For the base interaction, there is no evidence for a significant influence across subgroups. Including a three-way interaction to additionally test differences before and after the Kunming Declaration yields the following results. In the pre-Kunming period, green banks experienced lower influences of biodiversity news on CDS prices. In contrast, the impact is stronger for green banks in the post-Kunming period. These results are in line with the uncertainty reduction and risk perception effect acknowledged by Kölbel et al. (2022), before and after the declaration, respectively. Furthermore, the impact on US banks is studied separately, as the USA is the only United Nations (UN) member, which is not part of the CBD. Over the full sample, there is no evidence for diverging effects between US and non-US banks. However, before the Kunming Declaration, US-banks experienced increasing effects, which switch to decreasing impacts on the biodiversity-CDS relation in the post-Kunming period. The expectation of less stringent policies and regulations explains the lower impact on CDS spread changes in the post-Kunming period. The increasing effect before the declaration is not yet observed in the literature but might be caused by excessive financial distress due to natural disasters in the USA in the late 2010s. The cross-sectional differences before and after the Kunming Declaration are subject to potential multicollinearity concerns, which might affect regression outcomes. Therefore, they need to be treated with caution and are subject to further confirmation. More information will be provided in Chapter 6.2. To provide robustness, different tests are undertaken which account for data changes and irregularities. Furthermore, an alternative measure of a country's state of biodiversity will be employed. Given the heterogeneity of results for US and non-US banks, the baseline regression will also be estimated without US banks, to account for potential bias. The robustness checks overall confirm the presented results.

This thesis is structured as follows. Chapter 2 introduces important concepts of biodiversity and how its associated risks affect the financial sector. In Chapter 3, a literature review is conducted to provide a brief overview of related research papers and to highlight the scientific contribution of this thesis. Chapter 4 motivates the research hypothesis and introduces the econometric model. In Chapter 5, a description of the data is provided and in Chapter 6, the regression results are presented. In Chapter 7, additional analyses provide robustness checks for the presented results, and Chapter 8 concludes the thesis.

2 From Biodiversity Loss to Financial Risk

Dasgupta (2021) defines biodiversity simply as "the diversity of life" (p. 36). Described more specifically, it encompasses all ecosystems, as well as genetic variation and interaction within and between species. Additionally, many aspects of biodiversity can vary over time and therefore provide, together with genetic diversity, potential for evolution (Dudley, 2023). Valuing biodiversity is a challenge. According to Dasgupta (2021), ecosystems can be regarded as a third capital good, among human capital and produced capital. Biodiversity, however, is only a characteristic of natural capital and is therefore often disregarded when studying the value provision of nature. Dasgupta (2021) therefore defines six possibilities to value biodiversity, which blend into one another but can be distinguished. Fundamental value sources include the existence of humans, the existence of other species, as well as an intrinsic value of nature. Additionally, value can be derived from biodiversity's contribution to human health, as well as simple enjoyment of nature. These value sources have formed the basis for industries, like pharmaceuticals and ecotourism. The last source of value, which is mostly acknowledged in environmental and resource economics, are the goods and services available through nature. This source allows for an indirect valuation of biodiversity through studying industries that rely on the provision of such goods (Dasgupta, 2021). As biodiversity concerns increased in recent years, these estimations help to understand the effects global economies may face.

2.1 Risk Drivers of Biodiversity Loss

In a recent report by the WEF (2020), experts across academia, business, government, and the international community have been surveyed regarding their perceived global risks. Among other nature-related risks, biodiversity has been determined to be the 3^{rd} most severe in the long term. This comes to no surprise, as the rate of global nature change over the past 50 years is unprecedented in human history (IPBES, 2019). According to IPBES (2019), there are five direct global change drivers, which in turn result from indirect ones. Changes in land- and sea-use, direct exploitation of organisms, climate change, pollution, and invasive species can all be traced to human interactions, like production and consumption behaviors, technological innovation, or population dynamics.

Climate change being one of the risk drivers for nature change and therefore biodiversity loss, highlights an important aspect in their relation. Conceptually, biodiversity risks are different from climate-related risks. While biodiversity risk captures "the threats to the variety of life on Earth and its consequences, [...] climate risk relates to the potential negative consequences of a change in the climate system" Giglio et al. (2023, pp. 4–5). However, there exist important similarities and interdependencies between them. While both can result from similar direct change drivers, like deforestation and pollution, they don't necessarily have to. Indirect change drivers, however, are equal for both climate change and biodiversity loss (Pörtner et al., 2021). Importantly, both risks can amplify each other and drive climate and biodiversity degradation even further. Changes in temperature or CO_2 concentration, which are direct results of climate change, influence the working balance of ecosystems (Barger et al., 2018). In turn, biodiversity and functioning ecosystems are crucial to mitigate climate change. Global forest areas are crucial carbon storages, the loss of which counteracts climate change mitigation efforts and increases climate risk (McKinley et al., 2011). However, Giglio et al. (2023) show the importance of distinguishing both risks in the context of economic implications, as they follow different temporal patterns when quantified. Therefore, this thesis focuses on biodiversity risk only.

According to Dasgupta (2021), biodiversity risk can emerge through physical, transition, or litigation risk. Physical risks refer to the impact of ecosystem degradation on economies. Transition risk is caused either directly or indirectly, through misalignment with regulations, technological progress, or changes in consumer sentiment. Litigation risks occur if legal frameworks related to natural capital are breached. Independent through which channel these risks arise, they all affect global economies. According to the Organisation for Economic Co-operation and Development

(OECD), biodiversity risks will disseminate through global economies, initially through physical risks, by affecting industries which depend highly on ecosystem services (OECD, 2023a). Value chains could be disrupted, which leads to fluctuations and eventually an increase in systematic risk. This will materialize through microeconomic impacts, like business disruptions, and eventually macroeconomic consequences like growing inflation or deviating trade flows. Such alterations are directly linked to indirect change drivers and will increase spillover effects to other industries. Consequences of biodiversity loss will therefore not only affect those industries with direct exposure but various economic sectors (van Toor et al., 2020).

2.2 Biodiversity Risk in the Financial Sector

The financial industry is one of the economic sectors which will be indirectly affected by the consequences of biodiversity loss. As there is no significant direct dependency on ecosystem services, biodiversity-related issues materialize through financial risks instead of physical risks (Hudson, 2024; WEF, 2020). Macroeconomic changes impact financial risk drivers like market risk, operational risk, and credit risk (Dasgupta, 2021). Dasgupta (2021) provides an overview of how these risk drivers are affected by biodiversity loss. Market risk may be influenced by changes in economic conditions and devaluation of assets in consequence of physical ecosystem changes. Furthermore, market shifts and regulatory policies increase transition risk and affect financial performance and asset values. Operational risks arise from physical risks, such as disruption of supply chains through nature-related changes. Additionally, transitions in consumer sentiment toward sustainable practices may result in reputational damage. Lastly, financial institutions face credit risk, caused by potential losses in corporate lending if investees default on their credit obligations. Disruption of business operations or supply chains, caused by ecosystem degradation, can negatively influence asset quality and increase non-performing assets within lending portfolios. For financial institutions, this inflates both the probability of default and loss given default. Similarly, transition risks can disrupt business models, which reduces corporate earnings of investees, who may therefore not be able to meet their credit obligations.

In recent years, the severity of potential consequences of biodiversity loss for the financial sector in general has been acknowledged (Almeida et al., 2022; CBD Secretariat, 2021a; Hudson, 2024; OECD, 2023b). However, among financial institutions, exposure to credit risk is especially high for banks, as traditional business models strongly rely on customer loans (Bolívar et al., 2023). According to an estimation of the European Central Bank (ECB), companies with high reliance on at least one ecosystem service received about 75 percent of bank loans in the Euro area (Elderson, 2023). In the USA, bank loans worth 1.7 trillion dollars and bank securities worth 300 billion dollars were identified to be exposed to nature-related risks (Deloitte, 2024). Consequently, banks are particularly prone to credit losses and potential default of clients (Ahmad & Karpuz, 2024). Therefore, this thesis focuses on banks and aims to examine the effect of biodiversity losses on their credit risks.

3 Literature Review

This thesis contributes to different strands of literature. Firstly, it expands the literature on sustainability-related risk factors and their influence on credit risk, measured in CDS. These risk factors include, for example, carbon risk (Blasberg et al., 2024; Z. Zhang & Zhao, 2022), climate-related transition risk (Costola & Vozian, 2025; Ugolini et al., 2024), and corporate sustainability performance (Christ et al., 2022). Across the board, these factors are found to significantly impact CDS pricing. Kölbel et al. (2022) additionally examine whether the disclosure of physical and transitional climate risks influences CDS spreads. For the period after the Paris Climate Agreement in 2015, they detect that the disclosure of climate-related risks can have both positive and negative effects on CDS through either higher risk perception, or lower uncertainty. This thesis examines biodiversity risk as a new factor of sustainability-related risk, adding to the existing research on nature-related credit risk determinants.

Secondly, this thesis adds to the growing literature on the influence of biodiversity risk on the finance sector. An initial approach to estimate the impact of biodiversity loss on financial systems was introduced by van Toor et al. (2020). In a joint report by De Nederlandsche Bank and PBL Netherlands Environmental Assessment Agency, they introduce an approach to measure the magnitude of financial risk from biodiversity exposure. They use the ENCORE database, which maps different business processes and their reliance on ecosystem services, to categorize financial portfolios of Dutch financial firms. They find that 36% of the examined portfolios are highly or very highly reliant on ecosystem services, showing the potentially severe impact biodiversity loss can have on the Dutch financial system. This pioneering effort has since been replicated. For instance, Calice et al. (2021) use this approach to estimate the biodiversity exposure for Brazil and find that 46% of loans allocated by banks are highly or very highly dependent on ecosystem services. Similarly, Svartzman et al. (2021) adopt the methodology for the French financial system and find that 42% of the portfolios are dependent on ecosystem services. Another implementation of this approach is the study by Calice et al. (2023), who investigate emerging markets. They find that in those markets, banks allocate around 50% of their credit portfolio to firms with high or very high reliance on ecosystem services. They also show that this ratio is higher in low-income countries and lower for high-income countries.

There has also been an evolving literature studying whether biodiversity risks are priced in financial markets. Coqueret et al. (2025) use a biodiversity measure called Corporate Biodiversity Footprint (CBF) from Iceberg Data-Lab to construct portfolios going long on firms with a low biodiversity footprint and short on firms with a high footprint. When narrowing their analysis to sectors highly exposed to both physical and transition risk, they find that firms with a low biodiversity footprint realize higher returns. Additionally, they find that investors require a higher risk premium for assets with an excessive biodiversity footprint. This gap in expected returns has become more evident since the Kunming Declaration in 2021, which they argue with the increasing public awareness of biodiversity risks. Similarly, Garel et al. (2024) employ the CBF measure to examine stock returns by conducting an event study around the Kunming Declaration in 2021. They find that biodiversity is not priced in assets on average over their sample. However, after the external shock, firms experienced decreasing stock returns, which were more severe for firms with a high CBF. Their result also demonstrates investors' growing awareness of potential risks related to biodiversity since the Kunming Declaration and consequently a pricing of those risk factors in stock prices. Créti et al. (2024) follow a different approach in assessing the pricing of biodiversity in stock markets. They construct a new index from a "bio-capacity" and "bio-footprint" measure to relate a country's biodiversity richness to the damage inflicted upon it. On a firm level, they find a significant influence of physical biodiversity risks on profitability and stock returns. Additionally, Naffa and Czupy (2024) also find a biodiversity risk premium in stock markets. For their analysis, they use the MSCI's ESG scores to examine biodiversity performance on a firm level.

These approaches all rely on different data sources for biodiversity risk, all with their own shortcomings. The approach pioneered by van Toor et al. (2020) relies on the ENCORE database, which underestimates biodiversity reliance, as only first-order dependencies are considered (Calice et al., 2021). The CBF relies in large parts on estimates and sector averages to provide firm-level characteristics and is only available on an annual frequency (Garel et al., 2024). The measure introduced by Créti et al. (2024) only represents a country-level biodiversity resilience statistic, which does not capture the time-varying trends and developments contained in the measure of Giglio et al. (2023). MSCI's ESG score for biodiversity and land use mainly evaluates the management of the included risks and does not provide a criterion for the biodiversity exposure of external stakeholders (MSCI ESG Research LLC, 2023). When analyzing banks, such risks are important to assess their overall credit risk.

Giglio et al. (2023) recognize the need for a suitable quantification of both physical and transition risks. In their paper they, introduce text-based measures to quantify firm and industry-level biodiversity risks in the USA. Additionally, they construct a biodiversity news index, which quantifies the presence of biodiversity topics in New York Times articles. This indicator provides a comprehensive high-level risk measure, which mirrors overarching risks faced on a global scale. Using their firm-level metric, they find that biodiversity risks are already priced in equity markets. Based on this work, many papers investigating the effects of biodiversity risks on finance followed, which employ these measures. Kalhoro and Kyaw (2024) concudct an event study to show that around worldwide discussions on biodiversity risks, markets respond by adjusting firm valuations, depending on the risk exposure of industries and firms. Liang et al. (2024) find that a higher biodiversity risk exposure increases the crash risk of stocks. Ahmad and Karpuz (2024) show that firms with higher biodiversity risk vulnerability tend to gather higher cash reserves. Bach et al. (2024) analyze firms' performance and find that higher biodiversity risk negatively impacts growth and profitability. This thesis adds to this emerging body of biodiversity finance literature, which employs the risk measure by Giglio et al. (2023), by examining the effect of biodiversity risk on banks' CDS spreads.

Lastly, this thesis also contributes and extends initial approaches to examine the relationship between biodiversity risk and credit risk measured in CDS. Hoepner et al. (2023) investigate the impact of biodiversity, water scarcity, and pollution prevention on the financing conditions of infrastructure companies. They find that firms which manage these risks experience a significant decreasing effect on CDS slopes. They follow that the results suggest that these risks are perceived as long-term issues. Giglio et al. (2024) develop and empirically test a model to show how biodiversity influences economic output. In their analysis, they use the biodiversity news index developed by Giglio et al. (2023) to examine its effect on CDS spreads of government-issued bonds. They find that CDS spreads rise when negative news about biodiversity emerges. Furthermore, they show that this effect is weaker in countries with a superior state of biodiversity and a higher share of natural capital of overall wealth.

This thesis extends the work by Hoepner et al. (2023) and Giglio et al. (2024) by adapting their approach to the banking industry. In recent analysis on biodiversity finance, these firms are often excluded, leaving the effects of biodiversity on the banking industry relatively unclear (Créti et al., 2024; Liang et al., 2024). This thesis aims to close this gap.

4 Hypothesis Development & Econometric Model

As shown in Chapter 2, the effects of biodiversity loss affect financial institutions through several channels. Importantly, banks are sensitive to increasing credit risk because of their reliance on customer loans. This thesis examines whether biodiversity risk is significantly affecting credit risk in the banking industry.

As a measure of credit risk, CDS are used in this thesis. CDS are credit derivatives which serve as insurance in case of default of the underlying (Ericsson et al., 2009). In a CDS contract, the buyer pays a periodic premium called the CDS spread, which is denoted in basis points (bp) of its notional value (Zhu, 2006).[1] If the spread amount is denoted at 100 bp (1.0%), a buyer would need to pay a premium of $100,000 to insure debt with notional value of $10 million

[1] The spread and price of a CDS contract refer both to the premium paid by the buyer of the contract and are both used interchangeably throughout this thesis.

against default (Hasan et al., 2016). These premium payments are made either until maturity of the contract or the occurrence of a credit event (Blanco et al., 2005). Credit events include bankruptcy, obligation acceleration, obligation default, failure to pay, repudiation or moratorium, and restructuring (Zhu, 2006). In return for the premium payments, the seller of a CDS contract agrees to compensate the buyer for the losses incurred in case of a credit event (Ericsson et al., 2009). Therefore, CDS are a way to trade and also short credit risk, at a pre-defined price (Blanco et al., 2005). A bank's CDS spread therefore provides a measure of how its credit risk is perceived by the market (Wang et al., 2019). Compared to other credit risk measures, CDS provide distinct advantages. First, CDS contracts are homogeneous and standardized, which enables uniform usage in cross-country samples (Hasan et al., 2016). Additionally, the CDS markets respond more quickly to changes in credit risk and contain exclusive credit information, compared to bond yields (Blanco et al., 2005; Lee et al., 2018). CDS are also less affected by non-default components of risk, compared to bond spreads, which are more likely to be affected by contractual agreements and liquidity factors (Longstaff et al., 2005; B. Y. Zhang et al., 2009).

As a measure of biodiversity risk, this thesis employs the biodiversity news index by Giglio et al. (2023). In their paper, they recognize the need for adequate measurements and quantification of biodiversity risk. As a response to this issue, they develop a news-based biodiversity measure. The index is constructed by implementing a biodiversity dictionary, which includes biodiversity-related terms. New York Times articles are then analyzed to detect sentences which include at least one of the identified terms. To account for both negative and positive news about biodiversity risks, they determine the sentiment of each sentence by using the language model BERT. The number of positive news are then subtracted from the number of negative news, resulting in an index, where a higher value relates to more negative news. Focusing on newspaper articles has the advantage that current developments are quickly captured and asset markets reflect such news immediately (Giglio et al., 2024). But this process might cause the following shortcoming. Given only New York Times articles are considered, the index might over-represent biodiversity related topics, which are relevant to the USA but not on a global scale. Therefore, the question arises, whether the index is representative of global biodiversity concerns. However, Giglio et al. (2024) successfully apply the index to a global sample to investigate effects of biodiversity risks on sovereign CDS. Furthermore, this thesis addresses the potential issue by performing a robustness check, which excludes US banks to show that the obtained results are equally found for non-US banks and are therefore not driven by selection bias.

If credit risk in the banking sector is driven by biodiversity risks, this should be reflected in CDS pricing. During periods with negative news about biodiversity, the CDS spreads should react accordingly, as they are a measure of the market's bank credit risk perception (Wang et al., 2019). Therefore, the first tested hypothesis is the following:

> *Hypothesis 1. Bank's CDS spreads are positively related to biodiversity news and rise when negative news emerges.*

Following the Kunming Declaration in October 2021, biodiversity risks have received increasing global attention (Garel et al., 2024). Participating countries especially focused on the need to rethink the role of the financial sector regarding their investments and disclosure of biodiversity contributions (CBD Secretariat, 2021a). Similar to the Paris Agreement in 2015, the signing of the Kunming Declaration may encourage national and subnational policies, which increases transition risk (Almeida et al., 2022). Research has shown that impacts of biodiversity on the financial sector have been more severe after the Kunming Declaration (Garel et al., 2024; Kalhoro & Kyaw, 2024). Similarly, the increased perception of biodiversity risk following the Kunming Declaration may also influence the valuation of banks' credit risk. Therefore, a second hypothesis is tested:

> *Hypothesis 2. After the Kunming Declaration in 2021, the positive relationship between negative biodiversity news and banks' CDS spreads is more severe, compared to the pre-Kunming period.*

Giglio et al. (2024) find that the magnitude of biodiversity risk effects on CDS prices differs across countries. Characteristics like the state of biodiversity and the dependency on natural capital seem to influence how CDS react to negative news on a country level. For banks, the exposure to biodiversity risk is in part channeled through their credit portfolios (Hudson, 2024). Firms within these portfolios may experience varying effects, depending on their geological environment. Consequently, banks may experience heterogeneous impacts of increases in biodiversity risk, based on their location. Therefore, the following hypothesis is tested:

> *Hypothesis 3. The positive relationship of biodiversity news and bank's CDS spreads is stronger for banks located in countries with an inferior state of biodiversity.*

Transition risks affect banks through changes in market conditions. To mitigate this risk, they need to be open to adapting technological innovations and changing business processes (Dasgupta, 2021). Disclosing such intentions may be well received by market participants, which might influence CDS pricing. Kölbel et al. (2022) find that CDS markets respond to the disclosure of physical and transitional climate risks. For banks, there exist global initiatives, which aim to drive the adoption of sustainable practices and international agreements (Hudson, 2024). Adopting such initiatives may pose similar effects for banks, as those shown by Kölbel et al. (2022). Therefore, the following hypothesis is formulated:

> *Hypothesis 4. Banks which proactively acknowledge biodiversity risks experience lower impacts of such on their CDS spreads.*

The CBD consists of 196 member states, more than 100 of which have committed to implement the global biodiversity framework and engage in conservation efforts until 2030 (CBD, 2025; Garel et al., 2024). The USA is the only UN member to sign but not ratify the treaty to this day (Einhorn, 2025). Although there have been efforts towards biodiversity conservation, its influence on the agreements of the CBD is therefore limited. With the adoption of the global biodiversity framework in the context of COP 15, participating countries agreed to implement reporting obligations. These commitments are not legally binding, but have accelerating impacts on biodiversity-related regulation and litigation (Garel et al., 2024). Due to the lack of commitment of the USA to the global framework, the US economy and their banks might face lower transition risk due to the Kunming Declaration, which should be reflected in the relationship of biodiversity news and CDS price changes. Therefore, the following hypothesis is tested:

> *Hypothesis 5. Banks located in the USA experience lower effects of biodiversity news on CDS spreads after the Kunming Declaration in 2021.*

By adding country and bank characteristics to the analysis, this thesis aims to not only estimate the direct relationship between CDS and biodiversity risk but also to identify underlying drivers, which change the magnitude of those effects.

The baseline empirical design relies on panel regression to examine the relationship between CDS and biodiversity risks across entities and time. The regression is a multivariate OLS regression with different sets of fixed effects and clustered standard errors. It is estimated as follows:

$$CDS_{i,t} = \alpha + \beta_1 Biodiversity_t + \beta_2 X_{i,t} + \gamma_t + \mu_i + \varphi_j + \epsilon_{i,t} \quad (1)$$

The variable of interest $CDS_{i,t}$ denotes quarterly CDS returns for bank i at time t. The main explanatory variable $Biodiversity_t$ denotes the quarterly average of the biodiversity index by Giglio et al. (2023) at time t, which is invariant across banks and only varies over time. $X_{i,t}$ contains various bank and country characteristics as control variables. Bank characteristics include the leverage ratio, asset quality, bank size, funding stability, cost efficiency, and sensitivity to market risk. Furthermore, bank's equity return volatility is included in the analysis. For country characteristics, the stock index return and volatility, the slope of the yield curve, as well as the sovereign credit rating, are used. As fixed effects, time fixed effects γ_t, bank fixed effects μ_i and country fixed effects φ_j are employed. Lastly, α denotes the intercept, and $\epsilon_{i,t}$ the error term.

5 Data

Chapter 5 presents the data used in this thesis. First, the variables and their sources are described. Following, the unit root test is undertaken to account for non-stationarity. Lastly, the summary statistics of the sample are presented.

5.1 Variable Description

To create panel data for the banks in the analysis, CDS and the biodiversity index are merged with bank- and country-level control variables. Table 1 shows an overview of the variables included in the sample.

Data for CDS is available through Refinitiv Datastream. This database provides coverage of over 112,000 active CDS and further financial markets data (Refinitiv Datastream, n.d.). First, the available CDS are filtered to exclude inactive data series. Afterwards, all CDS of firms which are not banks, or which refer to sovereign debt, are excluded. CDS contracts can have different maturities as well as different restructuring clauses, which define under which circumstances changes to the debt obligations are considered a credit event (IHS Markit, 2021). Following Jorion and Zhang (2007), CDS with a 5-year maturity are used, as they are the most liquid and constitute the majority of contracts in CDS markets. Additionally, only those contracts are included, which cover senior unsecured debt and are denoted in US dollars. In contrast to Jorion and Zhang (2007), CDS data is not filtered regarding its restructuring clause. Following the financial crisis in 2009, the International Swaps and Derivatives Association (ISDA) redefined contractual characteristics, including changes to restructuring and credit events. Main protocols include the Big-Bang protocol from 2009 and ISDA 2014 definition modifications (Boyarchenko et al., 2019). Concluding these changes, different economic regions have adopted contracts with different restructuring clauses as their standard (Boyarchenko et al., 2019; IHS Markit, 2021). Contracts with full restructuring (CR) are mainly traded in Asia, contracts with modified-modified restructuring (MM) in Europe, and contracts with no restructuring (XR) in North America (IHS Markit, 2021). Furthermore, there are contracts with modified restructuring (MR), for which no specific region is mentioned by IHS Markit (2021). When constructing the sample, they are found to be implemented in CDS contracts for Australian banks and included accordingly. To account for these contractual changes and provide a global sample of banks, CDS contracts are therefore considered with all restructuring clauses. In case there exists CDS data with different restructuring clauses for the same bank, the contract is chosen, which is predominantly traded in the bank's country. In Appendix A.1, a list of CDS contracts and their restructuring clause is provided for the included banks. The result is a sample of CDS contracts for 75 banks. After excluding banks for which control variable data is not available, the total sample consists of 39 banks. CDS data considered in this thesis starts in the year 2015 to provide contractual conformity, as the 2014 definition changes to contractual terms by the ISDA came into effect in September 2014 (Boyarchenko et al., 2019).

Table 1: Variable Description

This table shows a description of the variables used in the sample, as well as the source and expected sign of the regression coefficient.

Variable	Description	Source	Expected Sign of Coefficient
CDS	Quarterly return of bank's CDS spreads	Refinitiv Datastream	
Biodiversity	Quarterly mean of the biodiversity index by Giglio et al. (2023)	Biodiversityrisk.org	+
Leverage	Ratio of total liabilities to the sum of total liabilities and total equity	Fitch Ratings	+
Asset Quality	Ratio of loan loss provisions to total loans	Fitch Ratings	+
Bank Size	Natural logarithm of total assets	Fitch Ratings	-
Funding Stability	Ratio of total deposits to total liabilities	Fitch Ratings	-
Cost Efficiency	Ratio of operating expenses to total revenue	Fitch Ratings	+
Sensitivity to Market Risk	Ratio of interest expenses to total liabilities	Fitch Ratings	+
Bank Volatility	Quarterly standard deviation of daily bank equity returns	Refinitiv Datastream	+
Stock Market Index Return	Quarterly return of a country's stock market index	Refinitiv Datastream	-
Stock Market Index Volatility	Quarterly standard deviation of daily stock index returns	Refinitiv Datastream	+
Yield Curve Slope	10-year government bond yield less 2-year government bond yield	Refinitiv Datastream	-
Sovereign Credit Rating	Index ranging from 1 (Fitch Ratings CCC rating) to 17 (Fitch Ratings AAA rating)	Fitch Ratings	-

Figure 1 shows the average daily CDS spread of the banks in the sample over the period between 2015 and 2023. The average spread of CDS in the sample was fluctuating between 60 and 180 basis points, with several periods of sharp increases. During the period between 2015 and early 2016, the average spread was rising, until it reached a maximum of about 176 basis points in February 2016. Additionally, spreads experienced a drastic rise from about 70 basis points to 145 basis points in early 2020. Furthermore, spreads were increasing drastically in the first months of 2022. When investigating these periods of sharply increasing CDS spreads in the past years, it becomes evident that CDS react to economic and global events. In early 2016, the price of oil had experienced the low point of a period of plunging prices from mid-2014 onwards (Stocker et al., 2018). This was followed by a slowdown in global growth, tighter fiscal policies, and increased credit risk for banks in the energy sector (Stocker et al., 2018; World Bank Group, 2016). Furthermore, the global COVID-19 pandemic, officially declared in early 2020, has damaged human lives, global economies, and credit conditions (Yin et al., 2022). Additionally, the Russian invasion of Ukraine in early 2022 imposed challenges on global supply chains and energy infrastructure, while also driving inflation, especially in the Euro area (Cui et al., 2023; Ferreira et al., 2025). While the sample in this thesis only includes a cross-section of global banks, the impacts of such events are still represented as spikes in the average CDS spreads. To account for such external shocks and to isolate their impact, time fixed effects are employed in the regression. However, the period of the COVID-19 pandemic will need to be handled with additional care. Compared to other times of crisis, the year 2020 has seen enormous spikes in economic uncertainty, similar in magnitude to the Great Depression of 1929-1933 (Baker et al., 2020). Through radical governmental measures, which were introduced to halt the spreading pandemic, firms experienced severe consequences on demand, revenue, and profitability, among others. The banking sector was among the hardest-hit sectors and reacted to increased uncertainty with a spike in CDS prices, as shown in Figure 1 (Apergis et al., 2022). Additionally, rising infection numbers induced these price increases (Hasan et al., 2023). Therefore, the pandemic and especially the year 2020 needs to be regarded as an exceptional period of crisis, in which CDS prices were significantly driven by pandemic metrics like confirmed cases and deaths (Apergis et al., 2022). Due to these factors, results of credit risk analyses during this period may be distorted. As a consequence, this thesis follows the approach by Blasberg et al. (2024), who exclude the year 2020 from their sample when examining the effect of carbon risk on CDS prices.[2]

[2] In Appendix A.5, regression results with the full sample are disclosed.

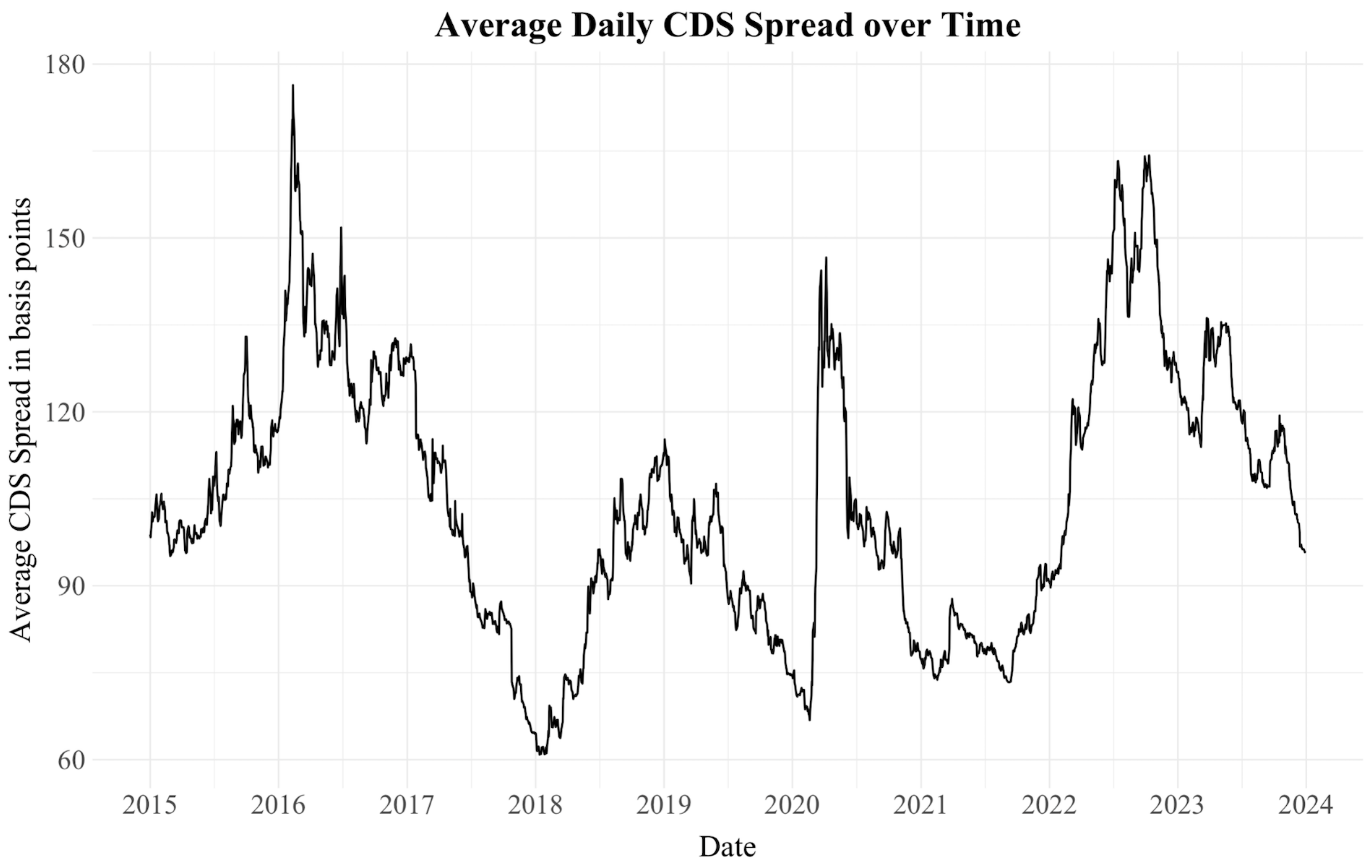

Figure 1: Average Daily CDS Spread of Banks in the Sample between 2015 and 2023.

This figure shows the daily mean of CDS spreads of the banks in the sample over the sample period between 2015 and 2023. The x-axis depicts the time and the y-axis the average CDS spread, which is depicted in basis points.

The data for the biodiversity index by Giglio et al. (2023) can be downloaded from *biodiversityrisk.org*. Observations of the index start in the year 2000 and end in 2023. For the period between 2015 and 2023, the average of daily index values is calculated for each quarter. A higher value of the biodiversity index is associated with a higher amount of bad news in the corresponding period. The biodiversity data is then merged with the CDS data for each bank. In Figure 2, the solid line shows the quarterly average of the biodiversity index. The dashed line depicts a fitted linear regression line, which shows the time trend of the biodiversity index. The graph shows the high fluctuation of the index over the sample period. Values range between 0.119 in Q3 of 2016 and 0.554 in Q3 2019 and Q3 2022. Across the sample period, the average biodiversity index is positive, which shows that news about biodiversity had a predominantly negative sentiment. Additionally, the slope of the fitted regression line is positive, which suggests that the biodiversity index takes on higher values in later periods of the sample.

Additionally, control variables are included, which have been shown to have significant effects on CDS of global banks (Drago et al., 2017; Hasan et al., 2016). First, balance sheet variables are included, which are available through Fitch Ratings. The leverage ratio is calculated as total liabilities divided by the sum of total liabilities and total equity. An increase in a bank's leverage ratio is expected to have increasing effects on CDS price changes (Hasan et al., 2016). Asset quality is a measure of quality and trends of a bank's major assets. It evaluates the management of credit risks, like the quality of loan underwriting or handling of non-performing assets (Hasan et al., 2016). Following Hasan et al. (2016), the loan loss provision ratio is considered as a measure for asset quality, which is defined as the ratio of loan loss provisions to total loans. An increase in the loan loss provision ratio is signaling lower asset quality, which is expected to increase CDS spreads. Bank size is included, as larger banks may be able to better diversify risk and may be deemed as too big to fail (Drago et al., 2017). As a measure for bank size, the natural logarithm of total assets is included. An increase in bank size is expected to decrease CDS spreads. Funding stability is included and measured by the ratio of deposits to total liabilities, as deposits are considered to be a stable source of funding (Drago et al., 2017). An increase in funding stability is therefore expected to be related to lower

While the baseline results do change, the overall findings of this thesis are supported. Please refer to the results in the appendix for more details.

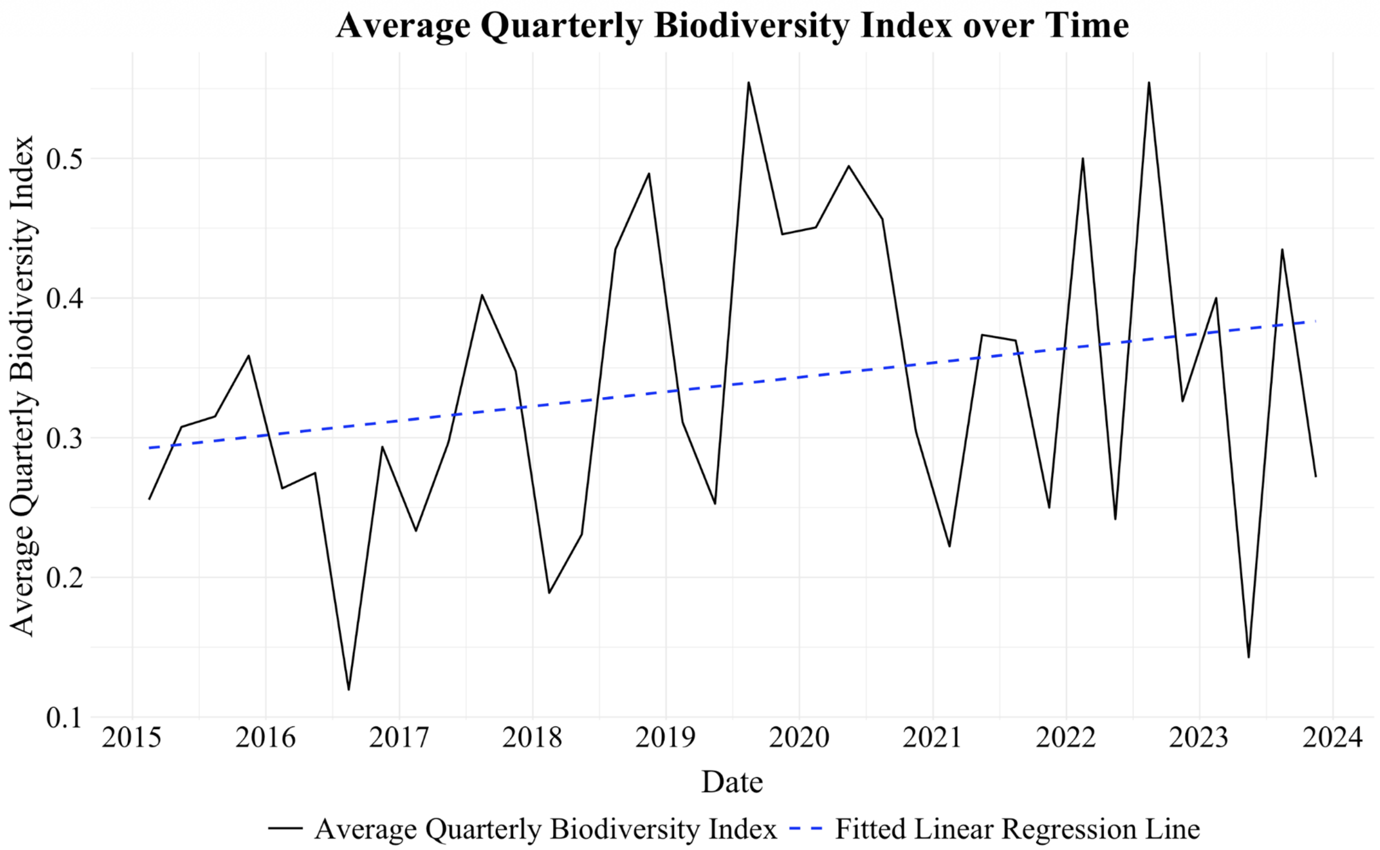

Figure 2: Average Quarterly Biodiversity Index between 2015 and 2023.

This figure shows the quarterly mean of the biodiversity index over the sample period between 2015 and 2023. The x-axis depicts the time and the y-axis the average biodiversity index. The dashed line depicts a fitted linear regression line, which shows the time trend of the average biodiversity index. The data points are displayed on the median day of each quarter.

CDS spreads. Additionally, cost efficiency is included as a measure of management quality. High-quality management helps to efficiently identify and navigate a bank's risks and ensure operation with low credit risk (Hasan et al., 2016). Cost efficiency is calculated as the ratio of operating expenses to total revenues, where a higher value shows less efficiency. Therefore, CDS spreads are expected to increase if the ratio increases. As the last balance sheet variable, sensitivity to market risk is included, which is the measure of sensitivity to shifts in interest rates for all loans and deposits. To account for this interest rate risk, cost of fund is included as a control variable, which is the ratio of interest expense to total liabilities. Banks with a higher cost of fund are considered to be more prone to changes in market conditions (Hasan et al., 2016). Increasing sensitivity to market risk is therefore expected to be associated with higher CDS spreads. Balance sheet variables are available for the 39 banks on a half-yearly basis. As the sample is constructed on a quarterly basis, the balance sheet variables are interpolated to match the quarters within a half-year period with the same value.

In addition, several market variables are included as control variables as well. First, a bank's equity returns are used to calculate its equity return volatility, which has been shown to have a significant impact on CDS prices (Hasan et al., 2016). It is calculated by taking the standard deviation of daily equity returns within a quarter. Higher equity volatility is associated with higher risk and should therefore increase CDS spreads (Tang & Yan, 2010). Additionally, stock index return is included to capture a country's business climate (Drago et al., 2017). Returns are calculated as the quarterly return of a country's stock index. Higher returns indicate a better business climate, which is expected to decrease CDS prices. Furthermore, the stock index return volatility is included, which is derived similarly to equity return volatility. Daily stock index returns are calculated, before their standard deviation within each quarter is derived. Similarly to equity return volatility, higher index volatility indicates greater economic uncertainty and default risk (Tang & Yan, 2010). A country's yield curve slope is calculated as the difference between the return on 10- and 2-year government bonds and is depicted in percent or basis points. It is also included as a control variable, as the slope is considered to be an economic indicator, where a higher yield curve slope suggests a better economic outlook (Hasan et al., 2016). Hence, a higher yield curve slope is expected to decrease CDS spreads. Additionally, sovereign credit ratings are included in the analysis,

Table 2: Panel Unit Root Test

This table shows the test results of the Fisher-ADF unit root tests by Choi (2001). Depicted are the dependent and explanatory variables as absolute values and as period change. Two tests are undertaken, the inverse normal test in the first two columns and the logit test in the last two columns.

Panel unit root test				
	Inverse normal		Logit	
	Statistic	P-value	Statistic	P-value
CDS	0.29	0.62	0.45	0.67
Δ CDS	-30.32	0.00	-52.11	0.00
Biodiversity	1.20	0.89	1.06	0.86
Biodiversity (standardized)	-37.50	0.00	-71.86	0.00
Leverage	4.37	1.00	4.30	1.00
Δ Leverage	-13.99	0.00	-18.60	0.00
Asset Quality	-1.05	0.15	-1.82	0.04
Δ Asset Quality	-12.98	0.00	-15.51	0.00
Bank Size	7.62	1.00	7.93	1.00
Δ Bank Size	-11.65	0.00	-14.13	0.00
Funding Stability	8.68	1.00	8.86	1.00
Δ Funding Stability	-15.23	0.00	-20.93	0.00
Cost Efficiency	-0.09	0.46	-0.66	0.25
Δ Cost Efficiency	-16.61	0.00	-25.81	0.00
Sensitivity to Market Risk	6.86	1.00	7.16	1.00
Δ Sensitivity to Market Risk	-7.62	0.00	-8.00	0.00
Bank Volatility	-0.52	0.70	1.22	0.89
Δ Bank Volatility	-41.12	0.00	-86.54	0.00
Stock Market Index Return	7.51	1.00	7.43	1.00
Δ Stock Market Index Return	-33.05	0.00	-58.42	0.00
Stock Market Index Volatility	-2.44	0.01	-2.20	0.01
Yield Curve Slope	-7.64	0.00	-7.61	0.00

where the credit rating assigned by Fitch Ratings is matched with a numeric scale. A full description of the rating scale is shown in Appendix A.2. As credit ratings are a depiction of a country's leverage and credit risk, a higher rating should be associated with a decrease in CDS prices. After accumulating all balance sheet and market control variables, they are merged with a bank's CDS data and the biodiversity measure. Country-level data is matched with each bank according to the location of its headquarters. All continuous variables except the biodiversity index and credit ratings are winsorized at the 1% and 99% levels to account for the influence of outliers (Garel et al., 2024). In total, the sample consists of 1,248 observations for 39 banks between 2015 and 2023, excluding the year 2020.

5.2 Unit Root Test

The variables of the sample may not be included as their absolute values, because of potential non-stationarity, where variables follow time-persistent trends. Stationarity, however, is important in the sense that estimated relationships should be stable over time when applying OLS regression (Wooldridge, 2020). Following Corò et al. (2013), the Fisher-ADF panel unit root test by Choi (2001) is used to examine the variables in the sample for unit roots. If they contain a unit root, it suggests that there exist time-persistent trends, which indicates non-stationarity. There are two unit root tests introduced by Choi (2001), called inverse normal and logit test. Both test that all entities contain a unit root as the null hypothesis against the alternative hypothesis that some do not (Corò et al., 2013). Table 2 shows the results of both unit root tests applied to the sample once in absolute values and once depicted as their period change. Credit ratings are not tested, as there exist entities without variation where the application of the unit root test is not feasible (Wooldridge, 2020). For p-values below 0.05, the

null hypothesis is rejected and the alternative hypothesis accepted, which implies stationarity. The results show clear indications that the null hypothesis is not rejected for all variables except stock market index volatility and yield curve slope. The other variables reveal non-stationarity and need to be transformed. All variables except biodiversity, stock index volatility, the yield curve slope, and credit rating are depicted as the period change in percent. For asset quality, the p-value is below 0.05 in the case of the logit test but above for the inverse normal test. As this result does not provide a clear implication, the following approach is taken. To ensure uniformity across balance sheet variables, asset quality is also included in the analysis as its period change. In robustness checks, it will be shown that including asset quality in absolute values provides similar results. The biodiversity

Table 3: Summary Statistics

This table shows the summary statistics for the variables used in the baseline regression. The sample includes a total of 1,248 quarterly observations for 39 banks between 2015 and 2023, excluding the year 2020. All variables except biodiversity and sovereign credit rating are winsorized at the 1% and 99% level.

Summary Statistics						
Baseline Sample $N = 1{,}248$	Mean	St. Dev.	Min	25th percentile	75th percentile	Max
Δ CDS (%)	1.779	22.787	-41.954	-13.212	10.383	80.107
Biodiversity (standardized)	0.000	1.000	-1.916	-0.692	0.680	2.100
Δ Leverage (%)	0.019	0.694	-1.928	-0.334	0.357	2.537
Δ Asset Quality (%)	-2.395	11.475	-31.456	-8.870	2.882	42.559
Δ Bank Size (%)	0.014	0.219	-0.692	-0.095	0.135	0.610
Δ Funding Stability (%)	0.960	5.076	-14.488	-1.498	3.071	18.731
Δ Cost Efficiency (%)	1.011	17.854	-44.007	-8.640	8.269	63.988
Δ Market Sensitivity (%)	19.196	53.077	-36.578	-5.614	21.753	329.719
Δ Bank Volatility (%)	2.785	33.423	-48.505	-19.880	20.427	113.394
Δ Index Return (%)	1.812	7.215	-15.412	-2.588	6.750	21.060
Index Volatility (%)	0.958	0.374	0.386	0.693	1.143	3.234
Yield Curve Slope	0.574	0.687	-2.058	0.216	1.079	2.018
Δ Sovereign Credit Rating	-0.020	0.189	-2.000	0.000	0.000	1.000

variable is standardized to remove non-stationarity, following Giglio et al. (2024). Credit Ratings are included as the absolute change in the numerical rating system (Corò et al., 2013). Stock market volatility, as well as yield curve slope, are already stationary and included as their absolute values. As shown in Table 2, all p-values are below 0.05 after the variable transformation. The null hypothesis can therefore be rejected, which provides evidence for the variables to be stationary.

5.3 Summary Statistics

Table 3 shows the summary statistics for the variables in the baseline sample, as they are used in the regression. The average CDS change per quarter is 1.779%, with a standard deviation of 22.787, which shows the large variation between periods where CDS increased and decreased within the sample. The biodiversity index is standardized to have a mean of zero and a standard deviation of one. For the balance sheet variables, the average period change was 0.019% for leverage, -2.395% for asset quality, 0.014% for bank size, 0.960% for funding stability, 1.011% for cost efficiency, and 19.196 % for sensitivity to market risk. The average change in volatility of daily bank equity returns is 2.785%. Changes in quarterly stock index returns were on average 1.812 % and their daily return volatility 0.958%. The yield curve slope was at 0.574 on average. Lastly, the average change in sovereign credit ratings is slightly negative, showing that there has been a surplus of credit rating downgrades during the sample period.

In Table 4, the pairwise correlation matrix for the sample is shown. Correlations are relatively low across the board. With the dependent variable CDS, correlations are in line with the expected directions for all variables, except for cost efficiency, yield curve slope, and sovereign credit rating. Correlation between equity and stock index variables is sometimes of concern (see Corò et al. (2013)), but not for the specification of this sample, as all correlations between bank return volatility, stock index return, and stock index volatility are not concerning.

6 Results

In Chapter 6, the results of the regression are presented. Chapter 6.1 presents the findings of the baseline regression, by introducing the different sets of variables step by step. First, the biodiversity measure is introduced, afterwards the balance sheet variables and lastly the market variables. Chapter 6.2 extends the baseline regression and introduces the Kunming Declaration as an external shock, to further examine the relationship between biodiversity news and CDS spreads. Chapter 6.3 examines the interaction effect of a country's state of biodiversity. In Chapter 6.4, the impact of adopting biodiversity-related bank initiatives on the relationship between CDS changes and biodiversity is tested. Lastly, Chapter 6.5 tests the relationship for banks in the USA.

6.1 Impact of Biodiversity News on Banks' Credit Risk

In Chapter 6.1, the influence of biodiversity news on CDS spread changes is examined to test *Hypothesis 1*. To analyze this relationship, a multivariate panel regression is conducted, initially using only the biodiversity measure. The regression formula is as follows:

$$\Delta CDS_{i,t} = \alpha + \beta_1 Biodiversity_t + \gamma_t + \mu_i + \varphi_j + \epsilon_{i,t} \quad (2)$$

The baseline regression is split into four separate parts. The analysis is conducted once without fixed effects and afterwards with time fixed effects, time and bank fixed effects, as well as time and country fixed effects. As the biodiversity measure only varies over time but not across banks, time fixed effects at the quarterly level would fully absorb its influence. Therefore, a higher frequency is chosen and time fixed effects are included on a half-yearly basis. This approach is in line with Giglio et al. (2024), who encounter the same issue and also resort to time fixed effects at a higher frequency. To account for autocorrelation, bank-level clustered standard errors are included. Results of the regression are shown in Table 5.[3] Column one shows the regression results without fixed effects. The coefficient of *Biodiversity* is positive, as expected in *Hypothesis 1*. The relationship is significant at the 1% significance level. An increase of one standard deviation in the biodiversity measure is associated with an increase in CDS spread changes by 1.946 percentage points with a standard error of 0.507. When including time fixed effects, the coefficient and standard error of *Biodiversity* increase to 4.231 and 0.795, respectively, while still being significant at the 1% significance level. With time fixed effects, an increase of one standard deviation of the biodiversity variable is now related to an increase in CDS price changes of 4.231 percentage points. In terms of model fit, time fixed effects increase the adjusted R^2 from 0.6% to 31.9% compared to column one. Including bank or country fixed effects does not change the results, as shown in columns three and four. The coefficient of the biodiversity measure stays robust and is significant across the board. Using additional fixed effects decreases the adjusted R^2 slightly. This is likely due to additional degrees of freedom being used by the fixed effects, without adding information to the model, which decreases the adjusted R^2 (Wooldridge, 2020).

Next, the balance sheet control variables are included in the analysis. The regression formula now changes to the following:

$$\begin{aligned}\Delta CDS_{i,t} = \alpha &+ \beta_1 Biodiversity_t + \beta_2 \mathrm{LEV}_{i,t} + \beta_3 \mathrm{AQ}_{i,t} \\ &+ \beta_4 \mathrm{Size}_{i,t} + \beta_5 \mathrm{FS}_{i,t} + \beta_6 \mathrm{CE}_{i,t} \\ &+ \beta_7 \mathrm{MS}_{i,t} + \gamma_t + \mu_i + \varphi_j + \epsilon_{i,t}\end{aligned} \quad (3)$$

$\Delta\mathrm{LEV}_{i,t}$ is the leverage ratio, $\Delta\mathrm{AQ}_{i,t}$ the asset quality, $\Delta\mathrm{Size}_{i,t}$ the bank size, $\Delta\mathrm{FS}_{i,t}$ the funding stability, $\Delta\mathrm{CE}_{i,t}$ the cost efficiency, and $\Delta\mathrm{MS}_{i,t}$ the market sensitivity. These variables are all included as their period change, as indicated by the preceding delta sign. For this regression, two different analyses are undertaken. First, the sample includes the balance sheet variables of the corresponding time periods without any adjustments. For the second analysis, a time lag is introduced for the balance sheet variables, following the argumentation of Drago et al. (2017) that information contained in such variables is not immediately available to the public. Therefore, a half-year time lag is introduced, which corresponds to the frequency of data availability. As banks conduct their operations during a half-year period, the results are made public in the following period. Since CDS prices are based on market perception, the information obtained from balance sheet variables may be reflected in price changes in the period after they occur. The summary statistics and correlation matrix presented in Chapter 5.3 cover the sample without time lag. The statistics only differ slightly for the balance sheet variables with time lag and are therefore disclosed in Appendix A.3 and A.4. For the regression with time lag, the econometric model changes to the following:

$$\begin{aligned}\Delta CDS_{i,t} = \alpha &+ \beta_1 Biodiversity_t + \beta_2 \mathrm{LEV}_{i,t-1} + \beta_3 \mathrm{AQ}_{i,t-1} \\ &+ \beta_4 \mathrm{Size}_{i,t-1} + \beta_5 \mathrm{FS}_{i,t-1} + \beta_6 \mathrm{CE}_{i,t-1} \\ &+ \beta_7 \mathrm{MS}_{i,t-1} + \gamma_t + \mu_i + \varphi_j + \epsilon_{i,t}\end{aligned} \quad (4)$$

Compared to formula (3), the balance sheet variables now capture the values of the previous time period $t-1$. Table 6 contains the results for the sample without time lag. Columns one to six show the stepwise introduction of the balance sheet variables using time fixed effects. Columns seven to nine show the results of the regression with all balance sheet variables and fixed effects. All regressions use clustered standard errors at the bank level to account for autocorrelation. The coefficient of *Biodiversity* is significant at the 1% level across all regressions. An increase of one standard deviation is associated with an increase in CDS price changes of 4.231 percentage points across the board, which is equal to the regression without balance sheet variables. Standard errors also remain stable across regressions and are comparable to the results presented in Table 5. All balance sheet variables are statistically insignificant across the board, which is unexpected, but left to be confirmed in the following baseline regression with all control variables. When comparing to the results in Table 5, the introduction of balance sheet variables does not increase the adjusted R^2 and hence the model fit. Furthermore, all coefficients, are in line with their expected sign, except ΔFS. However, since the coefficient is insignificant and the standard errors is relatively high, there is no evidence for a relationship in either direction. Table 7 shows the results of the regression with time-lagged balance sheet variables. The coefficient of biodiversity is unchanged compared to the results shown in Table 6. While all balance sheet variables are not significant, the introduction of the time lag changes the coefficients. Comparing columns seven to nine in Table 6 and Table 7 reveals the following changes. The sign of coefficient of the ΔFS variable now depicts the expected effect compared to the results without time lag. How-

[3] For the regressions throughout this thesis, significance levels at the 1%, 5%, and 10% levels are chosen, which are common in CDS literature. See, e.g. Corò et al. (2013), Giglio et al. (2024), Hasan et al. (2016), Hoepner et al. (2023), and Ugolini et al. (2024), and Z. Zhang and Zhao (2022) as references.

Table 4: Correlation Matrix

This table shows the pooled Pearson correlation for the variables used in the baseline regression. The sample includes a total of 1,248 quarterly observations for 39 banks between 2015 and 2023, excluding the year 2020. Depicted are the explanatory variables as used in the regression, winsorized at the 1% and 99% level.

Correlation Matrix														
Baseline Sample (N = 1,248)		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Δ CDS (%)	1.000												
(2)	Biodiversity (standardized)	0.085	1.000											
(3)	Δ Leverage (%)	0.107	-0.135	1.000										
(4)	Δ Asset Quality (%)	0.027	0.066	-0.083	1.000									
(5)	Δ Bank Size (%)	-0.134	-0.060	0.216	-0.104	1.000								
(6)	Δ Funding Stability (%)	-0.024	0.055	-0.218	-0.143	-0.211	1.000							
(7)	Δ Cost Efficiency (%)	-0.033	0.131	0.049	0.004	-0.178	0.082	1.000						
(8)	Δ Market Sensitivity (%)	0.058	0.177	-0.081	0.193	-0.043	-0.099	-0.020	1.000					
(9)	Bank Volatility (%)	0.317	0.161	0.054	0.055	-0.012	-0.035	0.000	0.015	1.000				
(10)	Δ Index Return (%)	-0.482	-0.180	-0.062	-0.054	0.106	0.025	-0.083	0.005	-0.229	1.000			
(11)	Index Volatility (%)	0.362	0.069	0.060	0.036	-0.100	0.016	0.004	0.098	0.353	-0.294	1.000		
(12)	Yield Curve Slope	0.062	-0.099	0.054	-0.327	0.006	0.067	-0.008	-0.350	0.028	-0.079	-0.070	1.000	
(13)	Δ Sovereign Credit Rating	0.039	-0.075	0.092	-0.065	0.005	-0.002	0.022	-0.014	0.027	-0.067	-0.040	0.192	1.000

Table 5: Baseline Regression with Biodiversity

This table displays the regression results of the relationship between biodiversity and CDS change with different fixed effects and clustered standard errors. Column 1 does not include fixed effects, while column 2 controls for time fixed effects, column 3 for time and bank fixed effects and column 4 for time and country fixed effects. CDS change is depicted in % change per quarter and the biodiversity measure is the standardized quarterly average of the biodiversity index. Clustered Standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)			
	(1)	(2)	(3)	(4)
Intercept	1.779***	9.137***	9.420***	8.941***
	(0.244)	(1.513)	(1.442)	(1.507)
Biodiversity	1.946***	4.231***	4.231***	4.231***
	(0.507)	(0.795)	(0.808)	(0.801)
Time Fixed Effects	No	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	No
Country Fixed Effects	No	No	No	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes
N	1,248	1,248	1,248	1,248
Adjusted R^2	0.006	0.319	0.302	0.313

ever, the coefficients of ΔLEV, ΔAQ and ΔCE are now negative, contradicting the expectation established in Chapter 5.1. While the insignificance does not indicate any relationship in either direction, the time lag does not seem to result in a better model fit. This claim is supported by the decrease in adjusted R^2 from 0.319 to 0.317 for the regression with all balance sheet variables and time fixed effects, compared to Table 6.

Next, the remaining control variables are included in the model. The regression formula changes as follows:

$$\begin{aligned} \Delta CDS_{i,t} = {} & \alpha + \beta_1 Biodiversity_t + \beta_2 \mathrm{LEV}_{i,t} + \beta_3 \mathrm{AQ}_{i,t} \\ & + \beta_4 \mathrm{Size}_{i,t} + \beta_5 \mathrm{FS}_{i,t} + \beta_6 \mathrm{CE}_{i,t} \\ & + \beta_7 \mathrm{MS}_{i,t} + \beta_8 \mathrm{BVOL}_{i,t} + \beta_9 \mathrm{IDXRET}_{i,t} \\ & + \beta_{10} \mathrm{IDXVOL}_{i,t} + \beta_{11} \mathrm{Yield}_{i,t} + \beta_{12} \mathrm{CR}_{i,t} \\ & + \gamma_t + \mu_i + \varphi_j + \epsilon_{i,t} \end{aligned} \tag{5}$$

$\Delta \mathrm{BVOL}_{i,t}$ is the change in bank volatility, $\Delta \mathrm{IDXRET}_{i,t}$ the change in quarterly stock market index return, $\mathrm{IDXVOL}_{i,t}$ the stock market index volatility, $\mathrm{Yield}_{i,t}$ the yield curve slope and $\Delta \mathrm{CR}_{i,t}$ the change in sovereign credit rating. Again, the regression is run both with and without a time lag for the balance sheet variables, to account for a potential delayed effect. The regression formula changes accordingly and compared to formula 5, the balance sheet variables are included from

Table 6: Baseline Regression with Biodiversity and Balance Sheet Variables

This table displays the regression results of the relationship between biodiversity and CDS change including balance sheet control variables without time lag. Columns 1 to 6 show the step-by-step introduction of balance sheet variables. Columns 7 to 9 show the full regression with time fixed effects, time and bank fixed effects and time and country fixed effects, respectively. The dependent variable is the quarterly change in CDS prices. Clustered Standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	9.138***	9.395***	8.875***	9.097***	9.450***	9.249***	9.453***	10.154***	9.353***
	(1.515)	(1.557)	(1.495)	(1.501)	(1.616)	(1.541)	(1.698)	(1.727)	(1.691)
Biodiversity	4.231***	4.231***	4.231***	4.231***	4.231***	4.231***	4.231***	4.231***	4.231***
	(0.796)	(0.796)	(0.796)	(0.796)	(0.796)	(0.796)	(0.797)	(0.810)	(0.803)
ΔLEV	-0.004						0.166	0.118	0.113
	(0.830)						(0.964)	(1.012)	(0.998)
ΔAQ		0.053					0.046	0.050	0.058
		(0.045)					(0.043)	(0.047)	(0.046)
ΔSize			-4.662				-3.811	-2.636	-2.306
			(2.910)				(2.966)	(3.649)	(3.489)
ΔFS				0.029			0.039	0.028	0.027
				(0.092)			(0.097)	(0.098)	(0.095)
ΔCE					0.041		0.037	0.041	0.041
					(0.035)		(0.037)	(0.038)	(0.037)
ΔMS						0.022	0.020	0.020	0.019
						(0.016)	(0.016)	(0.018)	(0.017)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	No	No	No	No	No	Yes	No
Country FE	No	No	No	No	No	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,248	1,248	1,248	1,248	1,248	1,248	1,248	1,248	1,248
Adj. R^2	0.318	0.319	0.320	0.318	0.319	0.320	0.319	0.302	0.313

the period $t-1$. Table 8 and Table 9 show the stepwise introduction of the market variables for both the regressions with and without lagged balance sheet variables. In Table 8, the variables $\Delta BVOL$, $\Delta IDXRET$ and *IDXVOL* are all significant at the 1% significance level once introduced. When comparing to the results in column seven of Table 6, the adjusted R^2 increases from 0.319 to 0.351, 0.388, and 0.340, respectively. Additionally, ΔCR is significant at the 10% significance level and slightly increases the model fit to 0.320. All coefficients are in line with the expected sign, except *Yield* and ΔCR. With time lag, the results stay similar, as shown in Table 9. The significance levels are all equal, except for ΔMS in column three. The coefficients and standard errors of all significant variables are comparable to the results without time lag. In terms of model fit, the regression with time lag underperforms in comparison, as the addition of market variables consistently leads to a slightly lower adjusted R^2, as already shown in Table 6 and Table 7. The full regression results are presented in Table 10. Panel A and Panel B include the results without and with time lag, respectively. In Panel A, *Biodiversity* is significant at the 5% significance level across all regressions. The coefficient is positive and between 1.532 and 1.559 with a standard error of 0.702 and 0.710. This also suggests economic significance, as an increase of one standard deviation in the biodiversity index is related to an increase in CDS spread changes by 1.532 to 1.559 percentage points.

Furthermore, $\Delta BVOL$ is significant at the 1% level with a coefficient between 0.094 to 0.101 and a standard error of 0.022. The effect of $\Delta BVOL$ on CDS spreads is therefore positive and an increase of 100bp is associated with an increase in CDS spread changes of 0.094 and 0.101 percentage points. Additionally, $\Delta IDXRET$ is also significant at the 1% level across all regressions. It is negatively related to CDS spread changes, as expected. The coefficient lies around -0.896 with a standard error of around 0.093. An increase in stock index returns by 100bp is therefore related to a decrease in CDS price changes of 0.896 percentage points. Lastly, *IDXVOL* is also significant at the 1% level and positively related to CDS price changes. For the results with time fixed effects only, the coefficient is 6.042 with a standard error of 1.524. Introducing bank or country fixed effects increases both statistics. The coefficient increases to 8.593 or 8.618 and the standard error to 2.250 or 2.224. Therefore, the economic impact of an increase in stock index volatility by 100bp is an increase in CDS spread changes between 6.042 and 8.618 percentage points. In contrast, none of the balance sheet variables are significant. Additionally, the coefficients of *Yield* and ΔCR are

Table 7: Baseline Regression with Biodiversity and lagged Balance Sheet Variables

This table displays the regression results of the relationship between biodiversity and CDS change including balance sheet control variables with time lag. Columns 1 to 6 show the step-by-step introduction of balance sheet variables. Columns 7 to 9 show the full regression with time fixed effects, time and bank fixed effects and time and country fixed effects respectively. The dependent variable is the quarterly change in CDS prices. Clustered Standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	9.138***	9.082***	8.984***	9.152***	9.209***	9.174***	8.894***	9.676***	8.840***
	(1.517)	(1.506)	(1.601)	(1.508)	(1.564)	(1.508)	(1.643)	(1.464)	(1.636)
Biodiversity	4.231***	4.231***	4.231***	4.231***	4.231***	4.231***	4.231***	4.231***	4.231***
	(0.796)	(0.796)	(0.796)	(0.796)	(0.796)	(0.796)	(0.797)	(0.810)	(0.803)
ΔLEV	0.006						-0.049	-0.109	-0.130
	(0.767)						(0.830)	(0.860)	(0.842)
ΔAQ		-0.014					-0.028	-0.031	-0.021
		(0.047)					(0.047)	(0.054)	(0.051)
ΔSize			-0.939				-1.533	-0.199	0.069
			(2.709)				(2.746)	(3.035)	(2.887)
ΔFS				-0.113			-0.126	-0.149	-0.149
				(0.096)			(0.104)	(0.114)	(0.111)
ΔCE					-0.008		-0.009	-0.006	-0.005
					(0.024)		(0.026)	(0.028)	(0.027)
ΔMS						0.006	0.005	0.004	0.004
						(0.014)	(0.014)	(0.015)	(0.015)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	No	No	No	No	No	Yes	No
Country FE	No	No	No	No	No	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,248	1,248	1,248	1,248	1,248	1,248	1,248	1,248	1,248
Adj. R^2	0.318	0.318	0.318	0.319	0.318	0.319	0.317	0.299	0.310

insignificant as well and indicate no significant relationship with CDS spread changes. The adjusted R^2 is 0.418, 0.406, and 0.415 for the regressions with the different fixed effects. Therefore, the model predicts 40.6% to 41.8% of the variance in CDS spread changes, which is comparable to Corò et al. (2013), who also study determinants of CDS spread changes. Panel B shows the results with lagged balance sheet variables. Compared to Panel A, the coefficients and standard errors of the significant variables are equivalent with only small deviations. Adding the time lag does not change the insignificance of the balance sheet variables. Concluding, there is therefore no evidence of a significant impact on CDS price changes for these variables. This result contrasts the studies of Drago et al. (2017) and Hasan et al. (2016). However, these studies employ a different empirical design, which might cause these result disparities. Both include CDS spreads in levels instead of period changes. While the balance sheet variables are shown to significantly determine the magnitude of CDS spreads in levels, this thesis shows that spread movements are not significantly affected by these measures. While Corò et al. (2013) show that changes in leverage do impact CDS price changes, they study corporate CDS in different industries. This thesis focuses on banks, which have a different liability structure where the leverage ratios are considerably higher and similar across different banks, which might explain the different results (Hasan et al., 2016). Therefore, the conclusions of this analysis do not contradict these

findings but rather add a new dimension to the analysis of bank's CDS determinants. Furthermore, these results also show that CDS spread changes are strongly influenced by the stock markets, which is in line with the findings of Norden and Weber (2009), who discover co-movements of stock and CDS markets, where stock returns lead changes in CDS spreads.

Concluding, the results of the regressions confirm *Hypothesis 1* and show that negative biodiversity news lead to increasing CDS spreads. The introduction of a time lag does not change the implications of the baseline regression. Therefore, it does not seem to capture anyother effects compared to the model without lag. Going forward, the sample without time lag will therefore serve as the basis in any further analysis.

Concluding, the results of the regressions confirm *Hypothesis 1* and show that negative biodiversity news lead to increasing CDS spreads. The introduction of a time lag does not change the implications of the baseline regression. Therefore, it does not seem to capture anyother effects compared to the model without lag. Going forward, the sample

Table 8: Stepwise Regression with all Control Variables without Time Lag

This table displays the regression results of the relationship between biodiversity and CDS change with the stepwise introduction of market control variables without time lag. Columns 1 to 5 show the step-by-step introduction of market variables with time fixed effects. The dependent variable is the quarterly change in CDS prices. Clustered Standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)				
	(1)	(2)	(3)	(4)	(5)
Intercept	9.341***	11.021***	-1.937	8.649***	9.595***
	(1.653)	(1.824)	(2.331)	(1.556)	(1.693)
Biodiversity	2.868***	2.584***	4.077***	4.175***	4.301***
	(0.767)	(0.751)	(0.731)	(0.779)	(0.781)
ΔLEV	-0.088	0.050	0.125	0.162	0.083
	(0.913)	(0.767)	(0.867)	(0.969)	(0.929)
ΔAQ	0.038	0.022	0.039	0.058	0.048
	(0.043)	(0.043)	(0.042)	(0.043)	(0.043)
ΔSize	-4.323	-3.222	-3.400	-3.836	-3.883
	(2.729)	(2.342)	(2.723)	(2.983)	(3.000)
ΔFS	0.050	0.063	0.013	0.042	0.038
	(0.090)	(0.100)	(0.094)	(0.096)	(0.097)
ΔCE	0.040	0.001	0.026	0.036	0.036
	(0.034)	(0.036)	(0.037)	(0.037)	(0.037)
ΔMS	0.019	0.019	0.025	0.021	0.019
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
ΔBVOL	0.131***				
	(0.023)				
ΔIDXRET		-0.971***			
		(0.110)			
IDXVOL			11.562***		
			(2.501)		
Yield				0.917	
				(0.759)	
ΔCR					3.900*
					(2.264)
Time FE	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	No	No	No
Country FE	No	No	No	No	No
Clustered SE	Yes	Yes	Yes	Yes	Yes
N	1,248	1,248	1,248	1,248	1,248
Adj. R^2	0.351	0.388	0.340	0.319	0.320

without time lag will therefore serve as the basis in any further analysis.

6.2 Impact of the Kunming Declaration

As introduced in earlier chapters, the Kunming Declaration represents a salient event for promoting biodiversity risk awareness in recent years. It has been adopted at the 15^{th} Conference of the Parties to the CBD (COP 15) on 13^{th} of October in 2021 (CBD Secretariat, 2021b). In the declaration, more than 100 countries announced their commitment to increase global biodiversity conservation efforts across all economic and societal sectors (Garel et al., 2024; Kalhoro & Kyaw, 2024). Especially the finance sector was mentioned, as sustainable financial flows and their voluntary engagement are needed to implement sustainable developments (CBD Secretariat, 2021b).

Due to the unexpected severity of outcomes, COP 15 can be viewed as a shock, which increased transition risks and uncertainty for global industries (Garel et al., 2024). Using this external shock, this thesis aims to determine whether the effect of biodiversity news on CDS prices changes with the Kunming Declaration. Recent studies have similarly used the declaration to examine how it influences biodiversity risk effects (Garel et al., 2024; Kalhoro & Kyaw, 2024). Due to the potential policy changes and increased risk uncertainty, the impact of the Kunming Declaration is expected to be positive. The effect of biodiversity news on CDS prices should therefore be higher for the periods following the declaration. To

Table 9: Stepwise Regression with all Control Variables with Time Lag

This table displays the regression results of the relationship between biodiversity and CDS change with the stepwise introduction of market control variables with time lag. Columns 1 to 5 show the step-by-step introduction of market variables with time fixed effects. The dependent variable is the quarterly change in CDS prices. Clustered Standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)				
	(1)	(2)	(3)	(4)	(5)
Intercept	8.932***	10.438***	-2.496	8.457***	8.975***
	(1.672)	(1.794)	(2.215)	(1.704)	(1.629)
Biodiversity	2.872***	2.567***	4.072***	4.201***	4.300***
	(0.767)	(0.758)	(0.730)	(0.778)	(0.781)
ΔLEV	0.135	-0.110	0.209	-0.025	-0.002
	(0.825)	(0.777)	(0.851)	(0.835)	(0.809)
ΔAQ	-0.021	-0.042	-0.044	-0.023	-0.023
	(0.048)	(0.048)	(0.045)	(0.047)	(0.049)
ΔSize	-1.317	-3.342	-0.069	-1.576	-1.973
	(2.570)	(2.562)	(2.932)	(2.773)	(2.732)
ΔFS	-0.137	-0.124	-0.132	-0.126	-0.122
	(0.099)	(0.111)	(0.104)	(0.105)	(0.106)
ΔCE	-0.012	-0.001	-0.024	-0.009	-0.009
	(0.027)	(0.024)	(0.027)	(0.026)	(0.026)
ΔMS	0.005	0.004	0.013	0.006	0.005
	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)
ΔBVOL	0.131***				
	(0.024)				
ΔIDXRET		-0.981***			
		(0.107)			
IDXVOL			11.984***		
			(2.434)		
Yield				0.494	
				(0.707)	
ΔCR					3.865*
					(2.242)
Time FE	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	No	No	No
Country FE	No	No	No	No	No
Clustered SE	Yes	Yes	Yes	Yes	Yes
N	1,248	1,248	1,248	1,248	1,248
Adj. R^2	0.348	0.388	0.338	0.316	0.317

incorporate this event in the sample of this thesis, a binary dummy variable $Kunming_t$ is constructed, with a value of one for the period of the Kunming Declaration and onwards and zero before. Interacting this variable with the biodiversity index will show if the baseline results change due to the external shock. The regression model is the following:

$$\begin{aligned} CDS_{i,t} =& \alpha + \beta_1 Biodiversity_t + \beta_2 Kunming_t \\ &+ \beta_3 Biodiversity_t \times Kunming_t \\ &+ \beta_4 X_{i,t} + \gamma_t + \mu_i + \varphi_j + \epsilon_{i,t} \end{aligned} \tag{6}$$

where the main coefficient of interest is β_3 of the interaction term. The term $X_{i,t}$ contains all control variables of the baseline regression. The results are reported in Panel A of Table 11. After adding the interaction term, *Biodiversity* is no longer significant. This suggests that there is no evidence for a significant relationship between biodiversity news and CDS spread changes before the Kunming Declaration. However, the interaction $Biodiversity \times Kunming$ is significant at the 5% significance level, with a positive coefficient of 2.179 and a standard error of 1.068 for the regression with time fixed effects only. Adding bank or country fixed effects decreases the coefficient slightly to 2.033 and 2.034, respectively. The relationship between biodiversity news and CDS prices is therefore sufficiently higher since the Kunming Declaration. On average, banks experienced CDS price changes which were 2.033 to 2.179 percentage points higher for every standard deviation increase of the biodiversity index, after the declara-

Table 10: Baseline Regression with all Control Variables

This table displays the regression results of the relationship between biodiversity and CDS change including all control variables without and with time lag. Panel A shows the results without and panel B with time lag. Columns 1 and 4 include time fixed effects, 2 and 5 time and bank fixed effects and 3 and 6 time and country fixed effects. The dependent variable is the quarterly change in CDS prices. Clustered standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)					
	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	4.117*	3.759	2.966	4.018	4.004	3.084
	(2.315)	(2.659)	(2.595)	(2.411)	(2.550)	(2.686)
Biodiversity	1.532**	1.556**	1.559**	1.541**	1.561**	1.563**
	(0.702)	(0.710)	(0.704)	(0.704)	(0.709)	(0.702)
ΔLEV	-0.163	-0.469	-0.474	0.198	0.027	-0.001
	(0.736)	(0.735)	(0.728)	(0.775)	(0.804)	(0.786)
ΔAQ	0.025	0.023	0.033	-0.037	-0.042	-0.030
	(0.043)	(0.046)	(0.045)	(0.049)	(0.054)	(0.051)
ΔSize	-3.471	-2.851	-2.451	-2.346	-1.365	-1.019
	(2.156)	(2.609)	(2.497)	(2.454)	(2.601)	(2.487)
ΔFS	0.058	0.035	0.033	-0.135	-0.162	-0.163
	(0.093)	(0.097)	(0.094)	(0.106)	(0.117)	(0.113)
ΔCE	-0.000	0.006	0.006	-0.013	-0.007	-0.006
	(0.034)	(0.036)	(0.035)	(0.024)	(0.025)	(0.025)
ΔMS	0.023	0.017	0.016	0.010	0.006	0.005
	(0.017)	(0.020)	(0.020)	(0.015)	(0.017)	(0.016)
ΔBVOL	0.101***	0.095***	0.094***	0.101***	0.095***	0.095***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
ΔIDXRET	-0.896***	-0.896***	-0.895***	-0.903***	-0.907***	-0.906***
	(0.093)	(0.093)	(0.092)	(0.092)	(0.094)	(0.093)
IDXVOL	6.042***	8.593***	8.618***	6.109***	8.420***	8.437***
	(1.524)	(2.250)	(2.224)	(1.564)	(2.317)	(2.290)
Yield	0.853	1.065	1.085	0.589	0.716	0.727
	(0.628)	(1.014)	(0.997)	(0.560)	(0.831)	(0.822)
ΔCR	0.064	0.331	0.325	0.075	0.248	0.232
	(2.609)	(2.696)	(2.671)	(2.452)	(2.543)	(2.522)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	No	Yes	No
Country FE	No	No	Yes	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,248	1,248	1,248	1,248	1,248	1,248
Adj. R^2	0.418	0.406	0.415	0.417	0.406	0.415

tion. The lack of significance of the *Biodiversity* variable may either be caused by a shortcoming in the model, which may not capture the existing effect, or correctly indicate its non-existence in the pre-Kunming period. The latter would be in line with the findings of Garel et al. (2024), who employ a different biodiversity measure and find increasing effects on stock returns only in the post-Kunming period. Furthermore, Coqueret et al. (2025) show similar results for the effect of biodiversity risks on asset prices. While not specifically using the Kunming Declaration as an external shock, they find that a negative premium has emerged since the year 2021. Concluding, the findings provide evidence in favour of the confirmation of *Hypothesis 2*. Following similar research, the results further indicate that the significant effect of biodiversity news on CDS spread changes has only occurred since the Kunming Declaration in 2021. Therefore, the relation proposed in *Hypothesis 1* and confirmed in Chapter 6.1 does not seem to hold for the full sample and is only evident in the post-Kunming period.[4]

Adding time fixed effects to a model with a time-dependent binary variable seems problematic at first glance, as they would normally absorb any invariant variable within a time period. However, since the time fixed effects are employed on a higher frequency, any variation within a half-year period is not absorbed. The binary *Kunming* variable switches to 1 in Q4 2021, as the declaration was signed in early October and therefore, there exists variation within a half-year period. Consequently, the variables, as well as the interaction, are not absorbed. To provide further transparency on this approach, Panel B reports the regression results without time fixed effects. Importantly, the interaction term is not affected and is comparable to the results obtained in Panel A. Furthermore, columns four and five show the importance of time fixed effects, as time shocks and trends are captured by the biodiversity and non-reported control variables in their absence. Using the half-yearly time fixed effects therefore improves the model's accuracy, as shown by the higher adjusted R^2 of the regressions in Panel A.

In the subsequent chapters, further country and bank characteristic will be included as interactions to test for heterogeneous cross-sectional effects. The regression will hereby differ between the two-way interactions with the biodiversity variable and a three-way interaction with the Kunming variable in addition. While the regression results in Table 11 suggest that the significant impact of biodiversity news on CDS prices only occurs after the Kunming Declaration, there might be mediating effects, which result in significant relationships prior to it. Therefore, the two-way interactions will be implemented to capture such effects over the full sample period. However, given the results from Table 11, it might also be the case that the relation is only occurring after the Kunming Declaration. In this case, bank and country characteristics might still instigate heterogeneous results across sub-groups in the sample, around the declaration. These will be captured by the three-way interactions. However, the inclusion of these regressions is not without problems. When interacting two variables X_1 and X_2, the interaction term $X_1 \times X_2$ is naturally somewhat collinear with the variables it is constituted of (Tate, 1984). This dependency between two or more variables is called multicollinearity, which given its presence violates OLS assumptions and obstructs its application (Alin, 2010; Wooldridge, 2020). The problems created by multicollinearity most importantly affect standard errors, which increase in magnitude and are more sensitive to small changes in the model (K. W. Smith & Sasaki, 1979). While the overall model significance is less affected, hypothesis testing for regression coefficients suffers from inflated p-values and possibly insignificant results in the presence of multicollinearity (Alin, 2010). Approaches to counteract these problems are often hard to realise, according to Wooldridge (2020). Increasing the sample size reduces uncertainty in standard errors but is constrained by data availability. Furthermore, excluding variables from the model may lead to biased estimates. A common approach to measure and become aware of potential issues is the Variance Inflation Factor (VIF), where a larger value of VIF_i indicates some form of involvement of variable i in linear dependencies (Alin, 2010). Commonly, a VIF greater than 10 is considered as problematic, but does not immediately invalidate results, as the cutoff value is determined rather arbitrarily (Alin, 2010; Wooldridge, 2020). For the three-way interactions in the following chapters, high VIF values are detected for some of the regressions and reported in Appendix A.6. The results are still included but should therefore be regarded with caution.

6.3 A Country's State of Biodiversity

As the prior regression indicates the existence of a significant relationship between biodiversity and changes in CDS prices since the Kunming Declaration, there might also exist dependencies with country characteristics, which change this relationship. Giglio et al. (2024) show that for sovereign CDS, a country's biodiversity characteristics and presence of natural capital change the magnitude of reactions to biodiversity news in CDS pricing. Similarly, this relation might exist on a bank level, as proposed in *Hypothesis 3*. To test this effect, the state of biodiversity within a country will be introduced to the model. As a measure for the state of biodiversity, the Environmental Performance Index (EPI) is implemented. Introduced by the Yale Center for Environmental Law & Policy, it captures the state of sustainability for countries around the world. It spans 58 performance indicators across 11 environmental pillars for more than 180 countries (Block et al.,

[4] The convention in Kunming was the first part of COP 15, with the second part taking place in December 2022 in Montreal. As a result, the Kunming-Montreal Global Biodiversity Framework was signed, where the intentions of the Kunming Declaration were formulated as specific targets. Garel et al. (2024) show that using the Montreal Agreement, instead of the Kunming Declaration, as an external shock, does not have the same effect on stock returns. They argue that the outcomes were possibly more widely expected and hence did not provide new information on firms' transition risks. While not reported, this thesis similarly finds that the Montreal Agreement did not affect CDS prices, contrary to the Kunming Declaration. However, it is necessary to note that the sample only includes relatively few observations after the Montreal Agreement was signed and may therefore lack explanatory power.

Table 11: Effect of Biodiversity News on CDS Price Changes following the Kunming Declaration

This table displays the regression results of the relationship between biodiversity and CDS change including the interaction of the Kunming dummy variable. Columns 1 to 3 show the full regression with time fixed effects, time and bank fixed effects and time and country fixed effects respectively. The dependent variable is the quarterly change in CDS prices. All control variables from the baseline regression are included. Clustered standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)				
	Panel A			Panel B	
	(1)	(2)	(3)	(4)	(5)
Intercept	3.871	3.666	2.873	-7.827***	-8.938***
	(2.401)	(2.806)	(2.737)	(1.856)	(1.676)
Biodiversity	0.176	0.286	0.288	-1.034*	-1.031*
	(1.152)	(1.173)	(1.163)	(0.569)	(0.564)
Kunming	4.388	4.119	4.115	4.587***	4.631***
	(3.314)	(3.405)	(3.373)	(1.020)	(1.009)
Biodiversity × Kunming	2.179**	2.033*	2.034*	2.156**	2.162**
	(1.068)	(1.072)	(1.062)	(0.849)	(0.840)
Control Variables	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	No	No
Bank FE	No	Yes	No	Yes	No
Country FE	No	No	Yes	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
N	1,248	1,248	1,248	1,248	1,248
Adj. R^2	0.418	0.407	0.416	0.321	0.331

2024). Each indicator receives a score and weight, which when aggregated form the overall EPI score. The EPI covers three main scopes, which are climate change, environmental health, and ecosystem vitality. For the analysis, the score of ecosystem vitality is used, which consists of indicators spanning the topics biodiversity & habitat, forests, fisheries, air pollution, agriculture, and wastewater. Through various indicators, it measures how well a country is managing their natural resources, while conserving biodiversity and ecosystems (Block et al., 2024). A higher score indicates a better ecosystem vitality for a given country. The EPI scores are available over different time periods. However, the latest publication from the year 2024 is used for the analysis in this chapter, as it contains new metrics related to the goals of the Kunming-Montreal global biodiversity framework (Block et al., 2024). The sign of the interaction term is expected to be positive, as negative news about biodiversity should have more dominant effects on CDS spreads in countries where ecosystem degradation is more advanced.[5]

The summary statistics of the global and unfiltered data are depicted in Table 12. The state of biodiversity variable is available for 181 countries and can range between zero and 100, where higher scores indicate better states of biodiversity. The mean is at 51.12 and the median at 49.60 with a standard deviation of 13.08. Furthermore, the values span between 22.70 and 83.10, showing that there is neither a country with a flawless state of biodiversity nor a country with a fully depleted one. In the regression, the state of biodiversity is included as a binary variable. This allows for a distinction between countries with superior and inferior biodiversity conditions, compared on a global scale. It is split at the median, where the variable takes on the value of one for countries with the inferior state of biodiversity. The binary variables are determined based on the entire available data, to avoid some countries being incorrectly allocated due to the limited number of countries in the sample. Determining the median based on all available country data avoids the possibility that a country with favorable biodiversity conditions is treated contrary in the regression and vice versa. After determining the binary variable, it is matched with the rest of the sample based on the location of a bank's headquarters. In the sample, seven banks are located in countries with a score below the median of 49.60. Details are provided in Appendix A.7.

The aim of the regression is to test the interaction effect of the introduced country characteristics and biodiversity on changes in CDS prices around the Kunming Declaration. Therefore, the three-way interaction between *Biodiversity*, *Kunming* and the country variable is estimated. The econometric model is as follows:

[5] Giglio et al. (2024) also employ a country's natural capital dependency to test for heterogeneous effects between biodiversity risk and CDS prices. For this thesis, the number of countries which have a high dependency is very low, as only three of 39 banks have scores above the median. This results in few observations and high potential for multicollinearity, which limits the robustness of results. Therefore, this measure is not included in the scope of this thesis.

Table 12: Summary Statistics of the State of Biodiversity Measure

This table shows the summary statistics for the state of biodiversity measure.

Summary Statistics								
Country Factors	N	Mean	St. Dev.	Min	25^{th} perc.	Median	75^{th} perc.	Max
State of Biodiversity	181	51.12	13.08	22.70	41.80	49.60	60.40	83.10

$$
\begin{aligned}
CDS_{i,t} = & \alpha + \beta_1 Biodiversity_t + \beta_2 Kunming_t \\
& + \beta_3 BioState_{med,i} + \beta_4 Biodiversity_t \\
& \times Kunming_t + \beta_5 Biodiversity_t \\
& \times BioState_{med,i} + \beta_6 Kunming_t \\
& \times BioState_{med,i} + \beta_7 Biodiversity_t \\
& \times Kunming_t \times BioState_{med,i} \\
& + \beta_8 X_{i,t} + \gamma_t + \epsilon_{i,t}
\end{aligned} \tag{7}
$$

where $BioState_{med,i}$ is the state of biodiversity variable. To provide robustness, the effect of the country characteristic is also estimated separately over the full sample, to show its effect independent of the Kunming Declaration. In terms of fixed effects, only time fixed effects are included, as bank or country fixed effects would fully absorb the time-invariant country characteristic. Table 13 reports the result of the regression. Column one shows the statistics of the regression with the two-way interaction and column two of the regression with the triple interaction. In column one, the coefficient of *Biodiversity* is positive and significant at the 5% significance level. The magnitude of the coefficient and standard error are slightly higher compared to the baseline regression presented in Table 10. $BioState_{med}$ is significant at the 5% significance level as well, indicating a relationship independent of *Biodiversity*, where CDS price changes were lower for countries with a worse state of biodiversity on average. The interaction term is insignificant and the standard error is rather high, which suggests substantial uncertainty and does not support any confident conclusion about an effect in either direction. With the introduction of *Kunming* in column two, *Biodiversity* becomes insignificant. Compared to Table 11, the interaction $Biodiversity \times Kunming$ is now insignificant, and with a p-value of 0.133 above the 10% significance threshold. Therefore, there is no resilient evidence for the existence of an effect of the interaction $Biodiversity \times Kunming$. Neither the interaction $Biodiversity \times BioState_{med}$, nor the triple interaction are significant. Hence, there is no indication that the effect of the Kunming Declaration is dependent on a country's state of biodiversity. *Hypothesis 3* can therefore not be confirmed, given the analysis for the sample in this thesis. The model fails to capture previously observed significant effects, which may be caused by two problems. First, the model may lack predictive power after introducing the triple interaction, since the sample is essentially split into four subgroups.[6] The sample size may therefore be too small to estimate a significant heterogeneous effect. Furthermore, the VIFs are exceeding the threshold of 10 in some cases, which may affect the results, as discussed in Chapter 6.2. Overall, the results show no evidence that CDS prices react differently to biodiversity news in countries with higher biodiversity degradation, neither before nor after the Kunming Declaration. Importantly, the results for $Biodiversity \times Kunming$ and $Biodiversity \times Kunming \times BioState_{med}$ do not necessarily contradict the effects obtained in Table 11. The lack of significance only fails to provide evidence for the according relations in this particular regression but does not prove their non-existence. To show robustness, the ecosystem vulnerability score from the Notre Dame Global Adaptation Initiative (ND-GAIN) database is used to provide an alternative measure of a country's ecosystem health. Regression results are disclosed in Chapter 7 and confirm the findings.

6.4 Membership in Bank Initiatives

As established in Chapter 2.2, the role of banks in the context of biodiversity loss has been increasingly acknowledged in recent years. In response to the emerging challenges, several banking initiatives have been formed, which aim to call for action and support collaboration among institutions. For example, the Finance for Biodiversity (FfB) Foundation has introduced a pledge, where all signatories aim to take on responsibility and support the conservation of biodiversity (FfB, 2024). In September 2023, the Task Force on Nature-related Financial Disclosures (TNFD) published a recommendation framework, which supports decision-making processes, risk management, and disclosure of nature-related risks. They urge the adoption of this framework to address insufficient risk management practices facing accelerating nature loss (TNFD, 2023). Furthermore, the UN Environment Program Finance Initiative (UNEP FI) has launched the Principles of Responsible Banking in 2019. While not exclusively focusing on biodiversity, the framework encourages sustainable finance in the areas of nature, climate, and circular economy among others (UNEP FI, 2024). More importantly, the

[6] Both binary variables *Kunming* and $BioState_{med}$ take on either zero or one. The triple interaction therefore estimates the four cases (0,0), (0,1), (1,0), and (1,1), where each bank is included in a subgroup based on its characteristics. Results are the coefficients of $Biodiversity$, $Biodiversity \times Kunming$, $Biodiversity \times BioState_{med}$ and $Biodiversity \times Kunming \times BioState_{med}$, respectively.

Table 13: Cross-Sectional Effect of Countries' State of Biodiversity

This table displays the regression results of the relationship between biodiversity and CDS change depending on the state of biodiversity and the Kunming Declaration. CDS change is depicted in % change per quarter and the biodiversity measure is the standardized quarterly average of the biodiversity index. The binary variable $BioState_{med}$ represents the state of biodiversity. Panel A includes the interaction effect of the state of biodiversity for the full sample and panel B dependent on the Kunming Declaration. All regressions include control variables and half-yearly time fixed effects. Clustered Standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)	
	(1)	(2)
Intercept	4.607*	4.172*
	(2.277)	(2.454)
Biodiversity	1.688**	0.473
	(0.660)	(1.172)
Kunming		4.454
		(3.263)
Biodiversity × Kunming		1.863
		(1.212)
$BioState_{med}$	-2.399**	-2.195*
	(1.003)	(1.168)
Biodiversity × $BioState_{med}$	-0.626	-1.135
	(1.140)	(0.986)
Kunming × $BioState_{med}$		-0.817
		(1.548)
Biodiversity × Kunming × $BioState_{med}$		1.386
		(2.035)
Control Variables	Yes	Yes
Time FE	Yes	Yes
Bank FE	No	No
Country FE	No	No
Clustered SE	Yes	Yes
N	1,248	1,248
Adj. R^2	0.418	0.418

framework provides guidance to promote setting biodiversity targets, to push their inclusion in banks' overall strategies, and to allocate responsibilities (UNEP FI, 2022). Banks are encouraged to halt financing of activities which are harmful to biodiversity and conduct robust risk mitigation and due diligence. The Principles for Responsible Banking are therefore an important step towards promoting biodiversity risk awareness in the banking sector (Hudson, 2024). By advocating these initiatives, banks openly acknowledge and engage with the potential issues of biodiversity risks. In recent years, studies have shown such decisions to impact the market perception of credit risks. Focusing on climate risks, Kölbel et al. (2022) and Carbone et al. (2021) both show that CDS markets react to the disclosure of climate risks twofold. While CDS spreads might rise due to increased risk perception, they might also decrease, since the disclosure lowers uncertainty. Furthermore, Kalhoro and Kyaw (2024) find that firms who actively manage biodiversity risks experience positive effects. Therefore, banks' participation in biodiversity initiatives is used to analyze whether they experience diverging effects of biodiversity risks on CDS prices, as proposed in *Hypothesis 4*. The above-mentioned initiatives are considered, as they specifically target financial institutions. The TNFD framework is ruled out, as banks have only started to adopt its recommendations as early as 2024, which lies beyond the scope of this thesis (TNFD, 2023). Furthermore, the FfB pledge has only one overlap between signatories and banks in the sample, which leads to insufficient observations. Therefore, only the UNEP FI initiative is considered. For each bank, a dummy variable is constructed, which is one for "green banks", which have joined the programs and zero for those which have not. The variable is constructed as time series data, which only includes a bank as green from the moment it joined. The members of the initiative and their date of adoption are disclosed on the UNEP FI website.[7] Of the total 39 banks, 18 have either been members over the full time period of the sample or have joined during. Analogous to the approach taken in chapter 6.3, the overall effect, as well as the effect before and after the Kunming Declaration, are tested. The regression model is the following:

[7] https://www.unepfi.org/members/.

$$\begin{aligned} CDS_{i,t} =& \alpha + \beta_1 Biodiversity_t + \beta_2 Kunming_t \\ &+ \beta_3 Green_{i,t} + \beta_4 Biodiversity_t \times Kunming_t \\ &+ \beta_5 Biodiversity_t \times Green_{i,t} \\ &+ \beta_6 Kunming_t \times Green_{i,t} \\ &+ \beta_7 Biodiversity_t \times Kunming_t \times Green_{i,t} \\ &+ \beta_8 X_{i,t} + \gamma_t + \epsilon_{i,t} \end{aligned} \tag{8}$$

where $Green_{i,t}$ is the introduced dummy variable for the banks which are members of the UNEP FI initiative. Table 14 shows the results of the regression. In column one, the baseline regression is extended by the interaction $Biodiversity \times Green$. The coefficient of *Biodiversity* is significant at the 5% significance level, with a slightly higher coefficient of 2.078 compared to the baseline regression. This suggests a significant effect for non-green banks, where a one standard deviation increase of the biodiversity index is related to an increase in CDS price changes of 2.078 percentage points. While the interaction term is negative, which would suggest lower effects of biodiversity news on CDS prices, it is insignificant. Therefore, there is no evidence that the observed effect of *Biodiversity* on non-green banks is divergent from green banks. Additionally, the adjusted R^2 is slightly lower compared to the baseline regression, which indicates that the interaction does not add any information to the model. For the triple interaction with Kunming, the results are given in column two. The coefficient of *Biodiversity* is insignificant, in contrast to the interactions $Biodiversity \times Green$ and $Biodiversity \times Kunming \times Green$, which are significant at the 5% and 10% significance level, respectively. Before the Kunming Declaration, green banks therefore experienced lower effects of biodiversity news on their CDS spreads, indicated by the negative coefficient of $Biodiversity \times Green$. This result is as expected and shows that acknowledging and engaging in risk management helps to reduce negative impacts on credit risk, in line with the uncertainty reduction effect hypothesized by Kölbel et al. (2022). After the Kunming Declaration, this effect switches. The positive coefficient of the interaction $Biodiversity \times Kunming \times Green$ indicates that CDS spreads of green banks have been impacted more strongly by biodiversity news in the post-Kunming period. This change is likely due to a higher risk awareness for the severe urgency and impacts of biodiversity risks after the Kunming Declaration raised awareness (Kölbel et al., 2022). For non-green banks, there is no indication of significant effects, as *Biodiversity* and $Biodiversity \times Kunming$ are insignificant. In conclusion, the regression results provide evidence that the relationship between biodiversity news and CDS prices is significantly different for banks who actively acknowledge and engage with their biodiversity risk exposure. Before the Kunming Declaration, green banks experience decreasing effects on CDS prices, which is in line with the uncertainty reduction effect. Afterwards, this relationship changes and green banks experience increasing effects, in line with the risk perception effect (Kölbel et al., 2022). The insignificance for non-green banks does not necessarily lead to the conclusion of a non-existence of any relationship. Rather, the model does not provide evidence for one, which may be caused by the sample distribution. Non-green banks are in large part located in the US, which may cause biased estimates. Note, the VIFs for the triple interaction are significantly lower compared to previous regressions. Only the VIF of Kunming is surpassing the threshold of 10, all others are below. Paired with moderate standard errors, the issue of multicollinearity therefore seems less threatening for this three-way interaction, but the results should still be treated with caution. Concluding, the results do not provide evidence for the confirmation of *Hypothesis 4*, given the regression over the full sample. Analyzing the effects for the pre- and post-Kunming period separately provides the expected results, which are in need of confirmation outside this thesis.

6.5 Impact on US Banks

Motivated by *Hypothesis 5*, another cross-section of the sample is analysed. Given that the USA is not officially part of the CBD, the Kunming Declaration may have diverging effects on the US economy, compared to countries which actively contributed to it. As the declaration may encourage policies and regulations, transition risks faced by banks and firms in the USA may be sufficiently lower (Garel et al., 2024). Consequently, banks' credit risk may be less affected by biodiversity risks. To test this hypothesis, a cross-sectional approach is used, by dividing the sample into banks located in the USA and those which are not. Following previous approaches, a binary dummy variable is introduced. The variable USA_i takes on the value one for every bank which is headquartered in the USA.

The regression formula is the following:

$$\begin{aligned} CDS_{i,t} =& \alpha + \beta_1 Biodiversity_t + \beta_2 Kunming_t + \beta_3 USA_i \\ &+ \beta_4 Biodiversity_t \times Kunming_t \\ &+ \beta_5 Biodiversity_t \times USA_i + \beta_6 Kunming_t \\ &\times USA_i + \beta_7 Biodiversity_t \times Kunming_t \\ &\times USA_i + \beta_8 X_{i,t} + \gamma_t + \epsilon_{i,t} \end{aligned} \tag{9}$$

The regression includes half-yearly time fixed effects, clustered standard errors, and the full set of control variables $X_{i,t}$. Table 15 presents the results of the regression. In column one, the results without the *Kunming* variable are shown. The coefficient of *Biodiversity* is positive and significant at the 10% significance level with a value of 1.410. Its standard error is slightly higher compared to the baseline regression with 0.777, indicating higher uncertainty of the estimate. The coefficient of USA_i is positive and significant at the 5% level, with a coefficient of 1.648. This result indicates that CDS spread changes where on average higher compared to non-US banks, independent of *Biodiversity*. The coefficient of the interaction is not significant, which suggests no evidence for heterogeneous effects of biodiversity news on CDS prices for US and non-US banks. Column two shows the results with the *Kunming* interaction. The coefficient of *Biodiversity* is insignificant.

Table 14: Cross-Sectional Effect of Sustainable Initiative Membership

This table displays the regression results of the relationship between biodiversity and CDS change including the interaction of the green bank and Kunming Declaration dummy variables *Green* and *Kunming*. Column 1 includes the regression without and column 2 with the Kunming interaction. CDS change is depicted in % change per quarter and the biodiversity measure is the standardized quarterly average of the biodiversity index. Both regressions include control variables and half-yearly time fixed effects. Clustered Standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)	
	(1)	(2)
Intercept	4.141*	4.292*
	(2.338)	(2.421)
Biodiversity	2.078**	1.245
	(0.846)	(1.258)
Kunming		4.003
		(3.525)
Biodiversity × Kunming		0.604
		(1.461)
Green	0.444	0.094
	(0.657)	(0.751)
Biodiversity × Green	-1.087	-2.626**
	(0.911)	(1.199)
Kunming × Green		0.637
		(1.273)
Biodiversity × Kunming × Green		3.529*
		(1.897)
Control Variables	Yes	Yes
Time FE	Yes	Yes
Bank FE	No	No
Country FE	No	No
Clustered SE	Yes	Yes
N	1,248	1,248
Adj. R^2	0.417	0.418

All three interaction terms $Biodiversity \times Kunming$, $Biodiversity \times USA$, and $Biodiversity \times Kunming \times USA$ are significant at the 1% level. First, the positive coefficient of 3.485 of $Biodiversity \times Kunming$ indicates that non-US banks have experienced stronger effects of biodiversity news on CDS price changes following the Kunming Declaration. The coefficient is economically significant, as for every standard deviation increase in the biodiversity index, CDS spreads are expected to increase by an additional 3.485 percentage points. Compared to the base Kunming interaction in Table 11 the coefficient is therefore substantially higher. Furthermore, the interaction of $Biodiversity \times USA$ is also positive with a coefficient of 2.593. It suggests that banks in the USA experienced stronger impacts of biodiversity news in the pre-Kunming period. In contrast, the coefficient of the interaction $Biodiversity \times Kunming \times USA$ is negative and with a value -5.190 of high economic significance. The result provides evidence that US banks experienced substantially lower effects of biodiversity news on CDS spreads following the Kunming Declaration. This may be caused by the expectation of no or less stringent policy and regulation changes following the global biodiversity framework compared to other countries, since the USA did not commit to the results of COP 15 as a non-member of the CBD. This result implies that transition risk plays a substantial part in the pricing of biodiversity risk in CDS spreads. A similar effect has been found by Kölbel et al. (2022), who study the effects of climate-related transition risks around the Paris Agreement. While CDS of firms in the USA were initially increasing, the withdrawal from the agreement by Donald Trump had decreasing effects on CDS, as the prospects of transition risk and new regulation disappeared. Concluding, the presented results lead to a confirmation of *Hypothesis 5*, as US banks face lower impacts of biodiversity risks after the Kunming Declaration, compared to non-US banks. Additionally, the results lead to a change in the confirmation of *Hypothesis 2*. While the Kunming Declaration did increase the impact of biodiversity news on CDS spreads, this effect does not persist for all cross-sections in the sample as banks located in the USA experienced contrary effects. *Hypothesis 2* can consequently only be confirmed for banks outside the USA.

To provide transparency, the VIFs for the three-way interaction are at times above the threshold of 10. While this might not have altered the observed effects, they should be

Table 15: Cross-Sectional Effect for US and non-US Banks

This table displays the regression results of the relationship between biodiversity and CDS change including the interaction of the USA and Kunming Declaration dummy variables *USA* and *Kunming*. Column 1 includes the regression without and column 2 with the Kunming interaction. CDS change is depicted in % change per quarter and the biodiversity measure is the standardized quarterly average of the biodiversity index. Both regressions include control variables and half-yearly time fixed effects. Clustered Standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)	
	(1)	(2)
Intercept	2.925 (2.333)	3.015 (2.435)
Biodiversity	1.410* (0.777)	-0.495 (1.201)
Kunming		5.027 (0.370)
Biodiversity × Kunming		3.485*** (1.232)
USA	1.648** (0.793)	2.261*** (0.605)
Biodiversity × USA	0.508 (1.005)	2.593*** (0.947)
Kunming × USA		-2.240 (1.723)
Biodiversity × Kunming × USA		-5.190*** (1.820)
Control Variables	Yes	Yes
Time FE	Yes	Yes
Bank FE	No	No
Country FE	No	No
Clustered SE	Yes	Yes
N	1,248	1,248
Adj. R^2	0.418	0.420

treated with caution. Currently left unexplained is the effect of biodiversity news on CDS prices for US banks before the Kunming Declaration. A comparable result has not yet been obtained in similar studies, to the current knowledge of the author. The following explanation of a potential cause is therefore not empirically observed and should be treated as such. According to the National Oceanic and Atmospheric Administration (NOAA), the decade between 2010 and 2019 has been a landmark period of climate disasters (A. B. Smith, 2020). According to A. B. Smith (2020), the USA experienced twice as many billion-dollar disasters, four of the five most costly natural disasters, as well as the two most severe wildfire seasons in USA history in the 2010s. Especially, the years 2016 and 2018 were hit by severe catastrophes, which resulted in sustained damages of several billion US dollars. In the year 2018, the USA was impacted by 14 separate billion-dollar disasters, representing the 4^{th} highest within a year, shortly after the year 2016 with 15 separate catastrophes (A. B. Smith, 2019). Matching these periods of severe environmental destruction with the biodiversity index shows that they coincide with predominantly negative biodiversity news, as shown in Figure 2. Giglio et al. (2023) illustrate that natural disasters like the California wildfires in 2018 can lead to substantial negative news coverage about biodiversity. Furthermore, Noth and Schüwer (2023) show that natural disasters negatively impact stability, credit quality, and profitability of banks in the USA. Given these dependencies, there is an argument to be made that the stronger effect of biodiversity news on credit risk for banks in the USA before the Kunming Declaration is caused by a period of unprecedented natural disasters.

7 Robustness Checks

In this chapter, several tests are included to provide robustness for the results presented in Chapter 6. First, the baseline regression is run with the absolute value of asset quality instead of its period change. In Chapter 5.2, the data of the sample was tested for stationarity to address time trends within the variables. Asset quality was transformed to the period change in the baseline sample despite being stationary already in one of the employed unit root tests. Therefore, Table 16 depicts the baseline regression with all control variables, including asset quality in levels instead of changes.

Table 16: Robustness Check with Asset Quality as Absolute Value

This table provides robustness checks for the baseline regression presented in Chapter 6 both with and without time lag. Panel A shows the results without time lag for the balance sheet variables and Panel B with time lag. Columns 1 and 4 show the regression with time fixed effects. Columns 2 and 5 show time and bank fixed effects and columns 3 and 6 time and country fixed effects. The dependent variable is the quarterly change in CDS prices. Clustered Standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)					
	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	3.879	4.715*	3.069	3.690	5.301**	3.544
	(2.329)	(2.592)	(2.523)	(2.421)	(2.410)	(2.559)
Biodiversity	1.552**	1.562**	1.560**	1.559**	1.571**	1.569**
	(0.702)	(0.712)	(0.707)	(0.704)	(0.710)	(0.703)
ΔLEV	-0.238	-0.493	-0.502	0.189	0.048	0.012
	(0.717)	(0.731)	(0.720)	(0.766)	(0.777)	(0.768)
AQ	-0.371	-0.315	-0.036	-0.443*	-0.506	-0.297
	(0.287)	(0.537)	(0.471)	(0.255)	(0.393)	(0.348)
ΔSize	-3.626	-3.098	-2.701	-2.240	-1.290	-0.943
	(2.171)	(2.594)	(2.509)	(2.506)	(2.605)	(2.489)
ΔFS	0.049	0.027	0.021	-0.124	-0.150	-0.155
	(0.097)	(0.100)	(0.098)	(0.109)	(0.119)	(0.115)
ΔCE	0.000	0.006	0.006	-0.011	-0.005	-0.005
	(0.034)	(0.035)	(0.034)	(0.024)	(0.026)	(0.025)
ΔMS	0.023	0.017	0.016	0.010	0.005	0.004
	(0.018)	(0.021)	(0.020)	(0.015)	(0.017)	(0.016)
ΔBVOL	0.099***	0.095***	0.095***	0.097***	0.094***	0.094***
	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
ΔIDXRET	-0.888***	-0.896***	-0.898***	-0.888***	-0.899***	-0.901***
	(0.091)	(0.093)	(0.092)	(0.091)	(0.095)	(0.093)
IDXVOL	6.976***	8.739***	8.561***	7.279***	8.823***	8.675***
	(1.891)	(2.349)	(2.314)	(1.852)	(2.352)	(2.322)
Yield	0.869	0.954	0.954	0.956	0.824	0.792
	(0.642)	(0.984)	(0.970)	(0.622)	(0.833)	(0.826)
ΔCR	-0.194	0.248	0.352	-0.151	0.148	0.184
	(2.628)	(2.779)	(2.745)	(2.437)	(2.579)	(2.552)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	No	Yes	No
Country FE	No	No	Yes	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,248	1,248	1,248	1,248	1,248	1,248
Adj. R^2	0.418	0.406	0.415	0.417	0.406	0.415

Panel A reports the regression without, and Panel B with the half-year time lag. Comparing the results to Table 10 shows no difference regarding the significant variables, as the coefficients and standard errors remain very similar. Briefly, *AQ* is significant at the 10% level in column 4, but not consistently across regressions. Additionally, the model fit stays similar across all columns as well. The potential issue of non-stationarity was therefore correctly evaluated, as changing the variable did not alter the results and ensured stationarity in the face of unclear results in the unit root test.

Next, a robustness check is provided to account for data irregularities which appeared during the construction of the dataset. The sample includes two banks, where the fiscal year is misaligned by one quarter. Therefore, their financial reports are not covering the same period compared other banks in the sample and their balance sheet variables are hence not perfectly in line with the rest of the variables. Additionally, stock data is not available in the home currency for one bank and is therefore included in US dollars instead, which may expose the data to exchange rate movements. These banks are included to provide a more comprehensive sample. To show that the data irregularities do not distort the regression results, Table 17 shows the baseline regression for the cross-section of the sample excluding the banks with diverging data availability. Again, Panel A does not include a time lag for the balance sheet variables, while Panel B does. Comparing the results to the baseline regression in Table 10 shows similar coefficients in terms of magnitude and significance. Only *Biodiversity* is significant at the 10% instead of the 5% significance level, while also having a lower coefficient compared to the baseline regression. Notably, $\Delta Size$ is briefly significant in column one, but not consistently across all regressions. Furthermore, the model fit is consistently lower compared to the baseline regression, indicating a smaller explanatory power of the model. The inclusion of the three banks has therefore positive effects for the model fit and coefficient robustness.

To provide robustness for the regression with country characteristics in Chapter 6.3, the ND-GAIN Ecosystem Vulnerability indicator is used to provide an alternative measure of a country's state of biodiversity. It assesses ecosystem vulnerability through the exposure, sensitivity, and adaptive capacity to changing nature conditions (Chen et al., 2024). It is one of six vulnerability components, which constitute the overall ND-GAIN index. The ecosystem vulnerability combines data on changes in biome distribution and marine biodiversity, dependency on natural capital, ecological footprint, share of protected biomes, and engagement in international conventions (Chen et al., 2024). Therefore, the score pro-

Table 17: Robustness Check excluding Banks with deviating Data Availability

This table provides robustness checks for the baseline regression presented in Chapter 6 both with and without time lag. Panel A shows the results without time lag for the balance sheet variables and Panel B with time lag. Columns 1 and 4 show the regression with time fixed effects. Columns 2 and 5 show time and bank fixed effects and columns 3 and 6 time and country fixed effects. The dependent variable is the quarterly change in CDS prices. Clustered Standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)					
	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.201**	4.934*	4.149	4.998*	4.985*	4.128
	(2.443)	(2.811)	(2.719)	(2.534)	(2.675)	(2.825)
Biodiversity	1.336*	1.360*	1.364*	1.340*	1.356*	1.356*
	(0.764)	(0.772)	(0.765)	(0.765)	(0.770)	(0.763)
ΔLEV	-0.285	-0.623	-0.644	0.259	0.063	0.023
	(0.858)	(0.865)	(0.856)	(0.931)	(0.983)	(0.961)
ΔAQ	0.031	0.035	0.045	-0.028	-0.028	-0.017
	(0.049)	(0.051)	(0.050)	(0.052)	(0.057)	(0.054)
ΔSize	-4.750**	-4.216	-3.740	-2.676	-1.792	-1.399
	(2.255)	(2.787)	(2.660)	(2.715)	(2.966)	(2.829)
ΔFS	0.046	0.024	0.022	-0.115	-0.138	-0.140
	(0.098)	(0.102)	(0.099)	(0.110)	(0.121)	(0.117)
ΔCE	0.014	0.020	0.021	-0.020	-0.015	-0.014
	(0.036)	(0.038)	(0.037)	(0.025)	(0.026)	(0.026)
ΔMS	0.018	0.011	0.010	0.009	0.005	-0.004
	(0.018)	(0.020)	(0.020)	(0.015)	(0.017)	(0.017)
ΔBVOL	0.099***	0.093***	0.092***	0.098***	0.092***	0.092***
	(0.023)	(0.024)	(0.024)	(0.023)	(0.024)	(0.024)
ΔIDXRET	-0.892***	-0.892***	-0.892***	-0.904***	-0.909***	-0.908***
	(0.098)	(0.098)	(0.098)	(0.097)	(0.099)	(0.099)
IDXVOL	5.572***	8.141***	8.183***	5.755***	7.915***	7.928***
	(1.568)	(2.348)	(2.322)	(1.572)	(2.374)	(2.346)
Yield	0.721	0.942	0.970	0.487	0.655	0.666
	(0.641)	(1.040)	(1.022)	(0.573)	(0.874)	(0.866)
ΔCR	0.188	0.458	0.454	0.211	0.387	0.365
	(2.617)	(2.706)	(2.681)	(2.408)	(2.499)	(2.480)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	No	Yes	No
Country FE	No	No	Yes	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,184	1,184	1,184	1,184	1,184	1,184
Adj. R^2	0.414	0.403	0.411	0.412	0.402	0.410

vides a suitable estimation of a country's state of biodiversity. The variable is constructed following the same logic as in Chapter 6.3, where a binary variable is introduced and split at the median of the full available dataset. Higher scores of the measure indicate a higher vulnerability and risk exposure. They are allocated the value one and lower scores the value zero. The country split is similar compared to $BioState_{med,i}$, but not the exact same, as otherwise the results of the robustness test would not differ from those obtained in Table 13. ND-GAIN data is available yearly from 1995 until 2022. For the variables used in the analysis, the scores are averaged between 2015 and 2022. Table 18 shows the summary statistics of the scores for the full dataset. The variable can range from zero to one. In the dataset, 182 country scores are available for ecosystem vulnerability.

The regression formula for the robustness test is equal to Formula 6, where $BioState_{med,i}$ is replaced with the variable of ecosystem vulnerability, $EcoVul_{med,i}$. The findings of the regression are depicted in Table 19. The statistics in column one confirm the result of Table 13, as there is no evidence for a significant influence on the relationship between biodiversity news and CDS spread changes. The results in column two further confirm that this non-relation with a country's state of biodiversity remains, both before and after the Kunming Declaration. Note that the ND-GAIN data is not available for one country which is included in the EPI. The number of ob-

Table 18: Summary Statistics of Alternative Country Biodiversity Characteristic

This table shows the summary statistics for the country biodiversity characteristic included in the robustness check for the regression of Chapter 6.3.

Summary Statistics								
Country Factors	N	Mean	St. Dev.	Min	25^{th} perc.	Median	75^{th} perc.	Max
Ecosystem Vulnerability	182	0.457	0.091	0.233	0.393	0.463	0.515	0.734

Table 19: Robustness Check with alternative State of Biodiversity

This table displays the regression results of the relationship between biodiversity and CDS change depending on the state of biodiversity and the Kunming Declaration. CDS change is depicted in % change per quarter and the biodiversity measure is the standardized quarterly average of the biodiversity index. The binary variable $EcoVul_{med}$ represents the ecosystem vulnerability. Column one includes the interaction effect of the alternative state of biodiversity for the full sample and column two dependent on the Kunming Declaration. All regressions include control variables and half-yearly time fixed effects. Clustered standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)	
	(1)	(2)
Intercept	5.604** (2.267)	5.624** (2.457)
Biodiversity	1.396* (0.736)	0.228 (1.237)
Kunming		4.514 (3.415)
Biodiversity × Kunming		1.953 (1.160)
$EcoVul_{med}$	-3.076*** (0.738)	-3.707*** (0.820)
Biodiversity × $EcoVul_{med}$	0.588 (0.867)	0.362 (1.049)
Kunming × $EcoVul_{med}$		0.410 (1.472)
Biodiversity × Kunming × $EcoVul_{med}$		0.221 (2.579)
Control Variables	Yes	Yes
Time FE	Yes	Yes
Bank FE	No	No
Country FE	No	No
Clustered SE	Yes	Yes
N	1,216	1,216
Adj. R^2	0.428	0.427

servations in Table 19 is therefore slightly lower at 1,216. While not reported, running the regression in Chapter 6.3 without the affected bank does not alter the results obtained in Table 13 and therefore does not interfere with the comparability of both country characteristics.

8 Conclusion

This thesis explores the relationship between biodiversity risk and bank's credit risk. Using a news-based biodiversity index by Giglio et al. (2024) for biodiversity risk and CDS as a measure of credit risk, a sample of 1,248 total observations for 39 global banks between 2015 and 2023 is constructed. This thesis finds evidence for a significant positive relationship between biodiversity news and CDS spread changes, where negative news leads to increasing CDS prices. Furthermore, the results show that equity return and volatility are dominating drivers of CDS spread changes. While balance sheet variables are shown to impact CDS price levels by similar studies, this thesis finds no evidence that this effect persists for CDS price changes.

Given the differences between US banks and non-US banks, the baseline regression will be conducted for a sub-sample. Excluding US banks will provide robustness for potential selection bias, as they constitute more than one quarter of the banks in the sample. The exclusion leads to increasing VIF estimates across all regressions. For two-way and three-way interactions, the test statistic indicates perfect multicollinearity between variables. Therefore, only the baseline regression will be tested. The results are presented

Table 20: Robustness Check for the Baseline Regression excluding US-Banks

This table provides robustness checks for the baseline regression presented in Chapter 6 both with and without time lag, by excluding US-banks. Panel A shows the results without time lag for the balance sheet variables and Panel B with time lag. Columns 1 and 4 show the regression with time fixed effects. Columns 2 and 5 show time and bank fixed effects and columns 3 and 6 time and country fixed effects. The dependent variable is the quarterly change in CDS prices. Clustered standard errors are given in parentheses and p-values are depicted as follows: (***) < 0.01, (**) < 0.05, (*) < 0.1.

	Δ CDS (%)					
	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.179**	1.124	0.595	4.527	0.626	-0.067
	(2.521)	(3.120)	(2.968)	(2.700)	(3.483)	(3.345)
Biodiversity	1.768*	1.701*	1.787*	1.726*	1.725*	1.725*
	(0.877)	(0.889)	(0.883)	(0.891)	(0.898)	(0.891)
ΔLEV	0.509	0.196	0.211	-0.397	-0.525	-0.529
	(0.864)	(0.853)	(0.845)	(0.744)	(0.754)	(0.742)
ΔAQ	0.027	0.027	0.033	-0.047	-0.055	-0.047
	(0.047)	(0.049)	(0.049)	(0.058)	(0.064)	(0.061)
ΔSize	-3.165	-1.282	-1.062	-5.204*	-3.372	-3.006
	(2.749)	(3.061)	(2.955)	(2.605)	(2.931)	(2.715)
ΔFS	0.054	0.034	0.032	-0.153	-0.173	-0.177
	(0.105)	(0.104)	(0.103)	(0.128)	(0.134)	(0.133)
ΔCE	-0.012	-0.008	-0.007	-0.006	-0.003	-0.002
	(0.038)	(0.039)	(0.039)	(0.025)	(0.026)	(0.026)
ΔMS	0.053*	0.053*	0.054*	0.008	0.007	0.008
	(0.026)	(0.028)	(0.027)	(0.018)	(0.020)	(0.019)
ΔBVOL	0.115***	0.112***	0.112***	0.114***	0.112***	0.112***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)
ΔIDXRET	-0.852***	-0.865***	-0.864***	-0.871***	-0.884***	-0.884***
	(0.100)	(0.102)	(0.101)	(0.097)	(0.101)	(0.100)
IDXVOL	6.037***	7.217***	7.225***	5.723***	6.749***	6.760***
	(1.335)	(2.026)	(2.006)	(1.489)	(2.221)	(2.192)
Yield	1.058	1.723	1.741	0.638	1.185	1.210
	(0.662)	(1.097)	(1.086)	(0.546)	(0.898)	(0.891)
ΔCR	2.947	3.334	3.326	3.087	3.266	3.236
	(2.843)	(2.892)	(2.874)	(2.591)	(2.662)	(2.642)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	No	Yes	No
Country FE	No	No	Yes	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
N	928	928	928	928	928	928
Adj. R^2	0.404	0.392	0.399	0.401	0.389	0.397

in Table 20. They reveal that the significance of variables from the baseline regression persists after excluding US banks. Bank volatility, as well as stock index returns and stock index volatility, are still significant at the 1% level. The biodiversity variable is significant at the 10% level instead of the 5% level seen in the baseline regression. However, as mentioned, the exclusion of US banks increased multicollinearity concerns, which may cause this change in significance through inflated standard errors. Additionally, the coefficient of *Biodiversity* is slightly higher compared to the baseline regression, as it increases from 1.532 to 1.768 in column one. This change also shows the heterogeneous effects for US and non-US banks over the sample period, as previously discussed in Chapter 6.5. Notably, for the non-US sample, market sensitivity is additionally significant at the 10% level. Overall, the implications of the results presented in Chapter 6.1 do not change when limiting the data to non-US banks, which provides evidence against a potential selection bias. Concluding, these tests have shown the robustness of the results obtained in Chapter 6.

Additionally, this thesis conducts several cross-sectional analyses to test for heterogeneous effects within the sample. The results show that the relationship persists for the period after the Kunming Declaration, suggesting no significant effect of biodiversity risk before. Furthermore, there exists no evidence for cross-sectional differences depending on a country's state of biodiversity or engagement in initiatives related to biodiversity conservation. Additional tests are undertaken to find heterogeneous results before and after the Kunming Declaration. A country's state of biodiversity does not change the relationship. In contrast, banks who engage in sustainability initiatives are found to experience lower effects of biodiversity risks in the pre-Kunming period and stronger effects afterwards. These results are conceptually in line with findings of Kölbel et al. (2022), who show a decreasing effect of climate risk on CDS before the Paris Agreement in 2015 and increasing effects afterwards, for firms who openly disclose their risk exposure. They account these effects to lower risk uncertainty before and higher risk perception effects after the external shock. This thesis further tests for heterogeneity between US and non-US banks, as the USA is the only UN nation which is not a member of the CBD. Before the Kunming Declaration, banks experienced a positive effect and afterwards a negative effect on the relationship between biodiversity risk and CDS, compared to banks located in other countries. The lower effects after the declaration are in line with the expectation of less stringent policies and regulations. The unexpected effects in the pre-Kunming period are yet unobserved to the knowledge of the author but may be explained by significant nature and climate-related disasters in the USA in the late 2010s, which had severe financial repercussions. The cross-sectional differences shown in the post-Kunming period are limited by a low number of observations, which might cause multicollinearity issues. The results are therefore left to be confirmed by similar studies. Overall, the findings of this thesis have important implications. First, banks are shown to be subject to biodiversity-related credit risks. Market participants have started to adapt CDS prices to emerging negative biodiversity news and require a higher spread since the Kunming Declaration. Therefore, banks need to consider biodiversity risks as a substantial part of their risk management processes. Furthermore, expectations of new policies and regulations following the Kunming Declaration spark the need for proactive risk management measures, as current business processes may be affected.

This thesis may provide a basis for further research. Studying the shown effects with more comprehensive samples might improve the robustness of the results. The biodiversity index by Giglio et al. (2023) currently does not provide data beyond 2023 and therefore constrains the sample of this thesis. The extension of the index would especially allow for more robust results for the period since the Kunming Declaration. Moreover, current developments, like the introduction of the TNFD framework, may be used to unveil the effects of biodiversity risk disclosure on the banking sector.

References

Ahmad, M. F., & Karpuz, A. (2024). Beyond climate change risk: Biodiversity and corporate cash holdings. *Economics Letters*, *236*. https://doi.org/10.1016/j.econlet.2024.111608

Alin, A. (2010). Multicollinearity. *WIREs Computational Statistics*, *2*(3), 370–374. https://doi.org/10.1002/wics.84

Almeida, E., Dikau, S., Le Calvar, E., Jun, M., Kunesch, N., Nicholls, M., Robins, N., Salin, M., Sun, T., & Svartzman, R. (2022). Central banking and supervision in the biosphere: An agenda for action on biodiversity loss, financial risk and system stability. *NGFS Occasional Papers*.

Apergis, N., Danuletiu, D., & Xu, B. (2022). CDS spreads and COVID-19 pandemic. *Journal of International Financial Markets, Institutions and Money*, *76*. https://doi.org/10.1016/j.intfin.2021.101433

Bach, T. N., Hoang, K., & Le, T. (2024). Biodiversity risk and firm performance. https://doi.org/http://dx.doi.org/10.2139/ssrn.4735012

Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). COVID-Induced Economic Uncertainty. *National Bureau of Economic Research Working Paper Series*, (26983). https://doi.org/10.3386/w26983

Barger, N. N., Gardner, T. A., Sankaran, M., Belnap, J., Broadhurst, L., Brochier, V., Isbell, F., Meyfroidt, P., Moreira, F., Nieminen, T. M., Okuro, T., Rodrigues, R. R., Saxena, V., & Ross, M. (2018). Chapter 3: Direct and indirect drivers of land degradation and restoration. In L. Montanarella, R. Scholes, & A. Brainich (Eds.), *IPBES (2018): The IPBES assessment report on land degradation and restoration* (pp. 137–218). Secretariat of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. https://doi.org/10.5281/zenodo.3237393

Blanco, R., Brennan, S., & Marsh, I. W. (2005). An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps. *The Journal of Finance*, *60*(5), 2255–2281. https://doi.org/10.1111/j.1540-6261.2005.00798.x

Blasberg, A., Kiesel, R., & Taschini, L. (2024). Carbon default swap – disentangling the exposure to carbon risk through CDS. https://doi.org/https://dx.doi.org/10.2139/ssrn.3856993

Block, S., Emerson, J. W., Esty, D. C., de Sherbinin, A., Wendling, Z. A., et al. (2024). 2024 Environmental Performance Index.

Bolívar, F., Duran, M. A., & Lozano-Vivas, A. (2023). Business model contributions to bank profit performance: A machine learning approach. *Research in International Business and Finance*, *64*, 101870. https://doi.org/10.1016/j.ribaf.2022.101870

Boyarchenko, N., Costello, A. M., & Shachar, O. (2019). The Long and Short of It: The Post-Crisis Corporate CDS. *FRB of New York Staff Report*, (879). https://doi.org/https://dx.doi.org/10.2139/ssrn.3334640

Calice, P., Diaz Kalan, F. A., Dunz, N. M. F., & Miguel Liriano, F. (2023). Biodiversity and Finance: A Preliminary Assessment of Physical Risks for the Banking Sector in Emerging Markets. http://documents.worldbank.org/curated/en/099526305022388443

Calice, P., Kalan, F. D., & Miguel, F. (2021). Nature-Related Financial Risks in Brazil. http://documents.worldbank.org/curated/en/105041629893776228

Carbone, S., Giuzio, M., Kapadia, S., Krämer, J. S., Nyholm, K., & Vozian, K. (2021). The low-carbon transition, climate commitments and firm credit risk. *ECB Working Paper*, *2021/2631*. https://doi.org/10.2139/ssrn.3991358

CBD. (2025). List of Parties.

CBD Secretariat. (2011). Convention on Biological Diversity - Text and Annexes.

CBD Secretariat. (2021a). Financial Sector Guide for the Convention on Biological Diversity - Key Actions for Nature.

CBD Secretariat. (2021b). Kunming Declaration.

Chen, C., Ian Noble, I., Hellmann, J., Coffee, J., & Murillo, M. (2024). University of Notre Dame Global Adaptation Initiative - Country Index Technical Report. https://gain.nd.edu/assets/581554/nd_gain_countryindex_technicalreport_2024.pdf

Choi, I. (2001). Unit root tests for panel data. *Journal of International Money and Finance*, *20*(2), 249–272. https://doi.org/10.1016/S0261-5606(00)00048-6

Christ, J., Hertel, T., & Kocian, J. (2022). Corporate Sustainability Performance and the Cost of Debt – An Analysis of the Impact of Country- and Industry-specific Climate Risk Exposures. https://doi.org/http://dx.doi.org/10.2139/ssrn.4135247

Coqueret, G., Giroux, T., & Zerbib, O. D. (2025). The biodiversity premium. *Ecological Economics*, *228*. https://doi.org/10.1016/j.ecolecon.2024.108435

Corò, F., Dufour, A., & Varotto, S. (2013). Credit and liquidity components of corporate CDS spreads. *Journal of Banking & Finance*, *37*(12), 5511–5525. https://doi.org/10.1016/j.jbankfin.2013.07.010

Costola, M., & Vozian, K. (2025). Pricing climate transition risk: Evidence from European corporate CDS. *Energy Economics*, *143*. https://doi.org/10.1016/j.eneco.2025.108248

Créti, A., Huang, Y., Jiang, B., & Sanin, M. E. (2024). Biodiversity Risk, Firm Performance, and Market Mispricing. https://doi.org/http://dx.doi.org/10.2139/ssrn.4765039

Cui, L., Yue, S., Nghiem, X.-H., & Duan, M. (2023). Exploring the risk and economic vulnerability of global energy supply chain interruption in the context of Russo-Ukrainian war. *Resources Policy*, *81*. https://doi.org/10.1016/j.resourpol.2023.103373

Dasgupta, P. (2021). The Economics of Biodiversity: The Dasgupta Review.

Deloitte. (2024). How banks can help achieve nature-positive outcomes and preserve biodiversity.

Drago, D., Tommaso, C. D., & Thornton, J. (2017). What determines bank CDS spreads? Evidence from European and US banks. *Finance Research Letters*, *22*, 140–145. https://doi.org/10.1016/j.frl.2016.12.035

Dudley, N. (2023). *Why Biodiversity Matters* (1st). Taylor & Francis Group. https://doi.org/10.4324/9780429346675

Einhorn, C. (2025). Far From Washington, Some Small Wins in the Fight to Protect Nature. *The New York Times*. https://www.nytimes.com/2025/02/27/climate/cop16-biodiversity-rome.html

Elderson, F. (2023). The economy and banks need nature to survive. *ECB*. https://www.ecb.europa.eu/press/blog/date/2023/html/ecb.blog230608~5cffb7c349.en.html

Ericsson, J., Jacobs, K., & Oviedo, R. (2009). The Determinants of Credit Default Swap Premia. *Journal of Financial and Quantitative Analysis*, *44*(1), 109–132. https://doi.org/10.1017/S0022109009090061

Ferreira, V., Abreu, A., & Louçã, F. (2025). The rise and fall of inflation in the Euro Area (2021-2024): A heterodox perspective. *Structural Change and Economic Dynamics*, *72*, 103–110. https://doi.org/10.1016/j.strueco.2024.12.004

FfB. (2024). Finance for Biodiversity - Reverse nature loss in this decade. https://www.financeforbiodiversity.org/wp-content/uploads/FinanceForBiodiversity_Guidance.pdf

Garel, A., Romec, A., Sautner, Z., & Wagner, A. F. (2024). Do investors care about biodiversity? *Review of Finance*, *28*(4), 1151–1186. https://doi.org/10.1093/rof/rfae010

Giglio, S., Kuchler, T., Stroebel, J., & Wang, O. (2024). The Economics of Biodiversity Loss. https://doi.org/10.3386/w32678

Giglio, S., Kuchler, T., Stroebel, J., & Zeng, X. (2023). Biodiversity Risk. https://doi.org/10.3386/w31137

Hasan, I., Liu, L., & Zhang, G. (2016). The Determinants of Global Bank Credit-Default-Swap Spreads. *Journal of Financial Services Research*, *50*(3), 275–309. https://doi.org/10.1007/s10693-015-0232-z

Hasan, I., Marra, M., To, T. Y., Wu, E., & Zhang, G. (2023). COVID-19 Pandemic and Global Corporate CDS Spreads. *Journal of Banking & Finance*, *147*. https://doi.org/10.1016/j.jbankfin.2022.106618

Hoepner, A. G. F., Klausmann, J., Leippold, M., & Rillaerts, J. (2023). Beyond Climate: The Impact of Biodiversity, Water, and Pollution on the CDS Term Structure [Swiss Finance Institute Research Paper No. 23-10, Michael J. Brennan Irish Finance Working Paper Series Research Paper No. 23-4]. https://doi.org/http://dx.doi.org/10.2139/ssrn.4351633

Hudson, R. (2024). Biodiversity and risk in the financial sector. *Journal of Sustainable Finance and Accounting*, *2*. https://doi.org/10.1016/j.josfa.2024.100009

IHS Markit. (2021). CDS Indices Primer.

IPBES. (2019). Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services.

Jorion, P., & Zhang, G. (2007). Good and bad credit contagion: Evidence from credit default swaps. *Journal of Financial Economics*, *84*(3), 860–883. https://doi.org/10.1016/j.jfineco.2006.06.001

Kalhoro, M. R., & Kyaw, K. (2024). Manage biodiversity risk exposure? *Finance Research Letters*, *61*. https://doi.org/10.1016/j.frl.2024.104989

Karolyi, G. A., & Tobin-de la Puente, J. (2023). Biodiversity finance: A call for research into financing nature. *Financial Management*, *52*(2), 231–251. https://doi.org/10.1111/fima.12417

Kölbel, J., Leippold, M., Rillaerts, J., & Wang, Q. (2022). Ask BERT: How Regulatory Disclosure of Transition and Physical Climate Risks affects the CDS Term Structure. Swiss Finance Institute Research Paper No. 21-19. https://doi.org/http://dx.doi.org/10.2139/ssrn.3616324

Lee, J., Naranjo, A., & Velioglu, G. (2018). When do CDS spreads lead? Rating events, private entities, and firm-specific information flows. *Journal of Financial Economics*, *130*(3), 556–578. https://doi.org/10.1016/j.jfineco.2018.07.011

Liang, C., Yang, J., Shen, L., & Dong, D. (2024). The role of biodiversity risk in stock price crashes. *Finance Research Letters*, *67*. https://doi.org/10.1016/j.frl.2024.105856

Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market. *The Journal of Finance*, *60*(5), 2213–2253. https://doi.org/10.1111/j.1540-6261.2005.00797.x

McKinley, D. C., Ryan, M. G., Birdsey, R. A., Giardina, C. P., Harmon, M. E., Heath, L. S., Houghton, R. A., Jackson, R. B., Morrison, J. F., Murray, B. C., Pataki, D. E., & Skog, K. E. (2011). A synthesis of current knowledge on forests and carbon storage in the United States. *Ecological Applications*, *21*(6), 1902–1924. https://doi.org/10.1890/10-0697.1

MSCI ESG Research LLC. (2023). MSCI ESG Ratings Methodology: Biodiversity & Land Use Key Issue.

Naffa, H., & Czupy, G. (2024). Biodiversity Risk Premium.

Norden, L., & Weber, M. (2009). The Co-movement of Credit Default Swap, Bond and Stock Markets: an Empirical Analysis. *European Financial Management*, *15*(3), 529–562. https://doi.org/10.1111/j.1468-036X.2007.00427.x

Noth, F., & Schüwer, U. (2023). Natural disasters and bank stability: Evidence from the U.S. financial system. *Journal of Environmental Economics and Management*, *119*. https://doi.org/10.1016/j.jeem.2023.102792

OECD. (2023a). A supervisory framework for assessing nature-related financial risks: Identifying and navigating biodiversity risks. *OECD Business and Finance Policy Papers*, *33*. https://doi.org/10.1787/a8e4991f-en

OECD. (2023b). Assessing biodiversity-related financial risks: Navigating the landscape of existing approaches. https://doi.org/10.1787/d52137a5-en

Pörtner, H. O., Scholes, R. J., Agard, J., Archer, E., Arneth, A., Bai, X., Barnes, D., Burrows, M., Chan, L., Cheung, W. L., Diamond, S., Donatti, C., Duarte, C., Eisenhauer, N., Foden, W., Gasalla, M. A., Handa, C., Hickler, T., Hoegh-Guldberg, O., & Ngo, H. T. (2021). Scientific outcome of the IPBES-IPCC co-sponsored workshop on biodiversity and climate change. B. IPBES secretariat, Germany. https://doi.org/10.5281/zenodo.4659158

Refinitiv Datastream. (n.d.). Refinitiv Datastream - The world's most comprehensive financial historical database.

Smith, A. B. (2019). 2018's Billion Dollar Disasters in Context. https://www.climate.gov/news-features/blogs/beyond-data/2018s-billion-dollar-disasters-context

Smith, A. B. (2020). 2010-2019: A landmark decade of U.S. billion-dollar weather and climate disasters. https://www.climate.gov/news-features/blogs/beyond-data/2010-2019-landmark-decade-us-billion-dollar-weather-and-climate

Smith, K. W., & Sasaki, M. S. (1979). Decreasing Multicollinearity: A Method for Models with Multiplicative Functions. *Sociological Methods & Research*, *8*(1), 35–56. https://doi.org/10.1177/004912417900800102

Stocker, M., Baffes, J., Some, Y. M., Vorisek, D., & Wheeler, C. M. (2018). The 2014-16 Oil Price Collapse in Retrospect: Sources and Implications. *Policy Research Working Paper*, (8419). http://hdl.handle.net/10986/29756

Svartzman, R., Espagne, E., Julien, G., Paul, H.-L., Mathilde, S., Allen, T., Berger, J., Calas, J., Godin, A., & Vallier, A. (2021). A 'Silent Spring' for the Financial System? Exploring Biodiversity-Related Financial Risks in France. *Banque de France Working Paper*, (826). https://doi.org/http://dx.doi.org/10.2139/ssrn.4028442
Tang, D. Y., & Yan, H. (2010). Market conditions, default risk and credit spreads. *Journal of Banking & Finance*, *34*(4), 743–753. https://doi.org/10.1016/j.jbankfin.2009.05.018
Tate, R. L. (1984). Limitations of Centering for Interactive Models. *Sociological Methods & Research*, *13*(2), 251–271. https://doi.org/10.1177/0049124184013002004
TNFD. (2023). Recommendations of the Taskforce on Nature-related Financial Disclosures.
Ugolini, A., Reboredo, J. C., & Ojea-Ferreiro, J. (2024). Is climate transition risk priced into corporate credit risk? Evidence from credit default swaps. *Research in International Business and Finance*, *70*. https://doi.org/10.1016/j.ribaf.2024.102372
UNEP FI. (2022). Principles for Responsible Banking - Guidance Document.
UNEP FI. (2024). 2023 Annual Overview.
van Toor, J., Piljic, D., Schellekens, G., van Oorschot, M., & Kok, M. (2020). Indebted to nature: Exploring biodiversity risks for the Dutch financial sector. https://www.dnb.nl/media/4c3fqawd/indebted-to-nature.pdf
Wang, D., van Lelyveld, I., & Schaumburg, J. (2019). Do Information Contagion and Business Model Similarities Explain Bank Credit Risk Commonalities? *ESRB: Working Paper Series*, (2019/94). http://dx.doi.org/10.2139/ssrn.3723456
WEF. (2020). Nature Risk Rising: Why the Crisis Engulfing Nature Matters for Business and the Economy. https://www3.weforum.org/docs/WEF_New_Nature_Economy_Report_2020.pdf
WEF. (2024). The Global Risks Report 2024 (19th Edition). https://www3.weforum.org/docs/WEF_The_Global_Risks_Report_2024.pdf
Wooldridge, J. M. (2020). *Introductory econometrics a modern approach* (Seventh). Cengage.
World Bank Group. (2016). Global Economic Prospects: Divergences and Risks. http://documents.worldbank.org/curated/en/588301469460261009
Yin, J., Han, B., & Wong, H. Y. (2022). COVID-19 and credit risk: A long memory perspective. *Insurance: Mathematics and Economics*, *104*, 15–34. https://doi.org/10.1016/j.insmatheco.2022.01.008
Zhang, B. Y., Zhou, H., & Zhu, H. (2009). Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms. *The Review of Financial Studies*, *22*(12), 5099–5131. http://www.jstor.org/stable/40468339
Zhang, Z., & Zhao, R. (2022). Carbon emission and credit default swaps. *Finance Research Letters*, *50*. https://doi.org/10.1016/j.frl.2022.103286
Zhu, H. (2006). An Empirical Comparison of Credit Spreads between the Bond Market and the Credit Default Swap Market. *Journal of Financial Services Research*, *29*(3), 211–235. https://doi.org/10.1007/s10693-006-7626-x

List of Abbreviations

bp Basis Points

CBD Convention on Biological Diversity

CBF Corporate Biodiversity Footprint

CDS Credit Default Swaps

COP 15 15^{th} Conference of the Parties to the Convention on Biological Diversity

CR Full Restructuring

ECB European Central Bank

EPI Environmental Performance Index

FfB Finance for Biodiversity

IPBES Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services

ISDA International Swaps and Derivatives Association

MM Modified-Modified Restructuring

MR Modified Restructuring

ND-GAIN Notre Dame Global Adaptation Initiative

NOAA National Oceanic and Atmospheric Administration

OECD Organisation for Economic Co-operation and Development

OLS Ordinary Least Squares

TNFD Task Force on Nature-related Financial Disclosures

UN United Nations

UNEP FI United Nations Environment Program Finance Initiative

VIF Variance Inflation Factor

WEF World Economic Forum

XR No Restructuring