

Essays on Sustainable Finance

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List of Abbreviations and Acronyms

AAR	Average Abnormal Return
CAR	Cumulative Abnormal Return
CAAR	Cumulative Average Abnormal Return
CBI	Climate Bond Initiative
CSR	Corporate Social Responsibility
CB	Conventional Bond
DCC	Dynamic Conditional Correlation
EBITDA	Earnings before Interest, Taxes, Depreciation and Amortization
EIB	European Investment Bank
ESG	Enviromental, Social and Governance
GB	Green Bond
HML	High Minus Low
ICMA	International Capital Market Association
IMF	International Monetary Fund
KPI	Key Performance Indicator
NPDC	Net Pairwise Directional Connectedness
NGO	Non-Governmental Organization
NSS	Nelson-Siegel-Svensson
SBTi	Science Based Targets initiative
SPT	Sustainability Performance Target
QQC	Quantile on Quantile Connctedness
QVAR	Quantile Vector Autoregression
SLB	Sustainabilty-Linked Bond
SMB	Small Minus Big
UN	United Nations
VIX	Volatiltiy Index

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1 General Introduction

Climate change poses systemic risks to the economy and the financial system—through both physical disruptions and the transitional challenges of shifting to a low-carbon economy. Financing this transformation requires mobilizing private capital at scale, positioning capital markets at the center of the transition. In response, a wave of ESG-labeled financial instruments has emerged.

This research focuses on the fixed-income segment of ESG-labeled instruments by evaluating how the market prices sustainability-linked bonds (SLBs), how equity investors react to their issuance, and whether these instruments can hedge climate risk.

SLBs are a novel class of ESG debt instruments that tie financial terms—typically coupon payments—to the achievement of predefined intermediate sustainability performance targets. If these targets are not met, a penalty mechanism is triggered—most commonly a coupon step-up applied for the bond’s remaining maturity. Unlike traditional green bonds, SLBs are not limited to project-specific financing. Instead, they aim to drive broader corporate sustainability by embedding accountability into general-purpose funding. Despite their growing issuance and policy relevance, research about SLBs is still in its infancy, especially when compared to the extensive body of work on green bonds. This gap underscores the need for empirical evidence on how these instruments are priced, perceived by markets, and function under climate-related financial stress.

Therefore, this work aims to answer the overarching research question: How are SLBs priced and perceived across financial markets, and what role do they play in managing climate-related financial risks?

To address this, I present three connected empirical studies that analyze SLBs from distinct but complementary perspectives: pricing behavior, investor perception, and their role in climate risk management.

- Paper 1 (“The Pricing of Sustainability-Linked Bonds on the Primary and Secondary Bond Market”) investigates yield differentials between SLBs and matched conventional bonds from the same issuer. It uses yield curve modeling via the Nelson–Siegel–Svensson method to infer issuance-day benchmarks, and fixed-effects panel regressions to analyze yield spreads on the secondary market. This paper has been published in the *Journal of Asset Management*.
- Paper 2 (“Generating Shareholder Value Through the Announcement of Sustainability-Linked Bond Issuance”) applies event study methodology to test whether SLB an-

nouncements are interpreted by equity markets as credible ESG signals, and whether such announcements generate abnormal returns for shareholders. This paper has been published in the Journal of Climate Finance.

- Paper 3 (“Climate Risk Spillovers and Hedging with ESG Assets”) evaluates the hedging effectiveness of SLBs and other ESG instruments during periods of heightened climate risk. Using vector autoregressions, GARCH modeling, and dynamic portfolio analysis, the study analyzes how these assets co-move with climate risk and whether they improve risk-adjusted returns in equity portfolios in times of elevated climate risk.

Together, these three studies provide a multi-angle view of how SLBs are integrated into financial markets. Each addresses a distinct component—debt pricing, equity investor interpretation, and portfolio-level climate risk exposure—but together they respond to the central question of how SLBs are valued, interpreted, and used. Their combined scope spans both fixed-income and equity markets, short-run announcements and risk dynamics. This integrative approach allows for a more complete understanding of SLBs in theory, in practice, and under financial stress.

Across the three studies, several core findings emerge:

- SLBs trade at a modest sustainability premium, suggesting that markets recognize their ESG value. However, this premium appears to be driven more by issuer credibility than by the strength of penalty mechanisms.
- Equity markets respond positively to SLB announcements, indicating that investors interpret them as credible sustainability commitments with long-term strategic implications. This reaction appears driven by a signaling effect, rather than the magnitude of the penalty or a greenium-related wealth transfer from bondholders to shareholders.
- SLBs and green bonds help hedge transition climate risk, positioning them as partial risk-reducing tools in diversified portfolios. However, they do not provide meaningful protection against physical climate risk—highlighting an important limitation in the current ESG asset universe.

These findings confirm theoretical predictions from modern ESG asset pricing models while also revealing nuances in how markets price, react to, and utilize sustainable finance instruments.

This work is grounded in asset pricing theories that explain how environmental, social, and governance (ESG) characteristics influence expected returns, risk exposures, and investor behavior. It draws particularly on the framework developed by Pastor, Stambaugh, and Taylor (2021), which proposes that green assets exhibit lower expected returns than brown assets due to two key mechanisms: Investor preferences (green taste), and hedging properties against climate risk. However, their model also predicts that green assets can exhibit higher realized returns than brown ones when investor sentiment shifts unexpectedly in favor of sustainability or during periods of elevated climate risk. In such scenarios, the demand for green assets rises sharply, pushing up their prices.

The first mechanism suggests that investors accept lower financial returns from holding SLBs, a phenomenon empirically observed as the “greenium”. In line with this, my first paper finds that sustainability-linked bonds (SLBs) trade at modest premiums of -4.68 bps (primary market) and -3 bps (secondary market) compared to matched conventional bonds. While this supports the existence of a greenium, the SLB structure complicates a pure taste-based interpretation: unlike green bonds, SLBs include performance-based financial penalties (coupon step-ups), making it unclear whether investors truly forgo returns as they receive compensation if the issuer fails to achieve its sustainability performance targets.

The second mechanism—hedging against climate risk—is confirmed in my last paper. Using dynamic correlation models and portfolio analysis, it is shown that SLBs and green bonds are more effective than other ESG instruments (such as clean energy equities) in hedging a broad equity portfolio against transition risk. This is consistent with the theory that green assets offer insurance-like benefits during periods of climate-related financial stress—and, as a result, may command lower expected returns in equilibrium, since investors are willing to pay a premium for protection. Moreover, the portfolio analysis reveals that adding SLBs and green bonds to an unhedged equity portfolio improves risk-adjusted performance—demonstrated by higher Sharpe ratios during periods of elevated climate risk. This supports the prediction by Pastor, Stambaugh, and Taylor (2021) that green assets can outperform brown ones when climate uncertainty or investor concern rises. However, neither SLBs nor other ESG assets function effectively as hedges against physical climate risk.

Finally, my second paper shows that the announcement of SLB issuance triggered statistically significant positive abnormal stock returns. This finding reflects a form of signaling: markets reward credible ESG signals. This aligns with signaling theory and provides further empirical support for the preference-shift mechanism described in Pastor, Stambaugh, and Taylor (2021), whereby green assets can generate higher realized returns during shifts in investor sentiment toward sustainability.

Taken together, these findings empirically support key theoretical mechanisms in sustainable asset pricing and demonstrate how SLBs operate at the intersection of market valuation, investor behavior, and climate risk management. Based on this, the dissertation makes three main contributions to the sustainable finance literature:

- Empirical clarity on SLB pricing: By comparing SLBs to matched conventional bonds using a yield curve fitting and panel regression framework, it offers the first estimates of SLB premia across both primary and secondary markets.
- Market perception and signaling: It is among the first to examine short-term equity market reactions to SLB announcements, providing evidence of signaling value and investor responsiveness to ESG-linked instruments.
- Climate risk management: It extends the understanding of climate risk transmission across asset classes, identifying SLBs and green bonds as partial hedges against transition risk—an insight relevant for investors designing climate-resilient portfolios.

Methodologically, a diverse set of tools including yield curve modeling, event studies, vector autoregressions, and DCC-GARCH models is applied, offering robust and multifaceted analysis across market settings.

The remainder of the dissertation is organized as follows:

Chapter 2 (“The Pricing of Sustainability-Linked Bonds on the primary and secondary bond market”) presents the first study, which investigates the pricing of sustainability-linked bonds in the primary and secondary bond markets. Chapter 3 (“Generating shareholder value through the announcement of sustainability-linked bond issuance”) analyzes short-term equity market reactions to SLB-issuance announcements through an event study framework. Chapter 4 (“Climate Risk Spillovers and Hedging with ESG Assets”) explores Climate Risk Spillovers and Hedging with ESG Assets effectiveness of ESG-labeled instruments—including SLBs—against physical and transition climate risks using forecast error variance decomposition, GARCH-modeling and portfolio analysis.

Together, these studies provide a comprehensive evaluation of sustainability-linked bonds as instruments that embed environmental accountability into financial contracts. By connecting pricing behavior, market perception, and climate risk dynamics, this dissertation advances the understanding of how capital markets are responding to the challenge of climate change through financial innovation.

2 The Pricing of Sustainability-Linked Bonds on the Primary and Secondary Bond Market

Abstract

This paper investigates the yield differentials between sustainability-linked bonds (SLBs)—a novel fixed income instrument whose coupon payments are linked to the achievement of predefined sustainable performance targets—and conventional bonds issued by the same company, both on the primary and secondary bond markets. By fitting yield curves with the Nelson–Siegel Svensson method on the SLB’s pricing day and applying panel regressions to examine yield differentials thereafter, the study assesses whether SLBs trade at a premium, indicating higher prices and consequently lower yields. Fixed-effects panel regression is utilized to isolate the unobserved time-invariant yield differential between SLBs and a matched synthetic conventional bond with the same residual maturity. The results show a statistically significant but economically small premium for SLBs in both the primary and secondary market. The sustainability premium is not significantly driven by the SLB’s penalty structure and fluctuates over time. This research contributes to the literature by applying a novel methodological framework to examine the evolving nature of SLB premiums and their implications for both issuers and investors.

Keywords: Sustainable finance, Green premium, Bond pricing, Sustainability-linked bonds, Socially responsible investing

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2.1 Introduction

Climate change is one of the most challenging issues of our time. Through physical risks, which cover environmental disasters and transitory risks, which are business-related risks that evolve due to societal and economical shifts toward a low-carbon future, climate change poses a risk to the economy and the financial system. This pushes for a fundamental conversion toward more sustainable production and consumption processes that require substantial investments. Asset markets will play a key role in financing the green transition and directing cash flows to companies with the best strategies and efforts to combat climate change and its consequences. Consequently, new financing instruments emerged in debt markets in recent years. After the first emission by the European Investment Bank (EIB) in 2007, the growth of green bonds soared, and this trend is likely to hold in the future (Flammer, 2021). Moreover, additional types of sustainable debt in terms of social and sustainable bonds (GSS; green, social and sustainable bonds in the following) have been issued until today. In 2022, GSS bonds had an issuance volume of 795 billion USD according to Refinitiv’s ESG Bond Guide Database. Reflecting the growing importance of ESG-related debt, the academic literature started focusing on the pricing of green bonds, particularly the extent to which green bonds trade at a premium—which is referred to as “greenium”, where prices of green assets are higher (and consequently yields lower) compared to conventional bonds. Evidence in this field in favor of green premiums—“greenium”—has been mixed so far (e.g., Kapraun et al., 2021). Although the increased transparency and acceptance of GSS bonds might lead to lower bond yields on the primary and on the secondary market, the lack of a uniform definition of eligible projects would dampen the credibility of the market leaving its net effect on bond returns unclear (Bundesbank, 2019). Besides, particularly green bonds sometimes lack the criterion of “additionality”, because they refinance existing projects and assets but not representing an innovative beyond “business as usual” trajectory to reduce greenhouse gas (GHG) emissions (Maino, 2022). Finally, green bonds taxonomies do not extensively include some “hard-to-abate” sectors like energy or manufacturing which, however, have high debt capital requirements to prefinance the sustainable conversion of the production process.

In response to these limitations, sustainability-linked bonds, SLBs in the following, have emerged as novel and alternative fixed income instrument offering a different approach to sustainable finance. Unlike GSS bonds, which restrict financing to specific environmentally beneficial projects (e.g., renewable energy, energy efficiency or pollution prevention),¹ SLBs offer issuers the flexibility to finance general-purpose initiatives while

¹For an overview of eligible projects, see the Green Bond Principles of the ICMA: <https://www.icmagroup.org/assets/documents/Sustainable-finance/2022-updates>

committing to measurable sustainability targets. Those targets, which can relate to environmental, social or governance outcomes, create financial incentives for issuers to meet predefined sustainability goals. Nonachievement of those targets leads to varying financial characteristics, most commonly coupon step-ups (ICMA, 2020). This makes SLBs particularly attractive for companies aiming to integrate sustainability across their operations, while providing investors with a framework that holds issuers accountable. Given the maturity of the green bond market and the mixed evidence regarding the existence of a “greenium,” the shift to investigating SLBs is essential. Their flexible approach requires empirical examination to understand how financial markets price SLBs compared to conventional bonds. The International Capital Market Association (ICMA), which serves as the secretariat to the SLB-principles, made two key provisions for how SLBs can address the critics green bonds are confronted with (Vulturius et al., 2022). First, SLBs are intended to finance general-purpose projects that have company-wide sustainability objectives, prioritized by the sustainable target a company selects. In particular, sustainability performance targets (SPT) should be beyond a “business as usual” trajectory, related to science-based scenarios (like the Science-Based Target Initiative, SBTi) or policy targets (Paris Agreement). Past performance of the issuer against a key performance indicator should be reported over a period of at least three years in addition to the relevance and positioning of the sustainable performance target against industry peers. Secondly, the novel SLB-penalization scheme should incentivize the issuer’s effort to reach its targets and signal investors that the issuer credibly attempts to dampen the negative consequences arising from climate change.²

Despite their potential, recent industry reports stress growing investor skepticism toward SLBs.³ Some are accused of greenwashing, might it be due to unambitious sustainable performance targets or a coupon step-up being not punitive enough. For instance, Tesco’s SLB, linked to the reduction of greenhouse gas emissions, only covers 2% of its total emissions. US-based Level 3 Communications \$900 million SLB maturing in 2029 can be redeemed by the investor in January 2024 before any penalty of not achieving the sustainability targets kicks in. Altogether, such loopholes undermine the credibility of the market and weaken investor confidence.

Considering these challenges and given the flexibility and potential of SLBs to incentivize company-wide sustainability, this paper aims to investigate how SLBs are priced in comparison with conventional bonds. It is assessed whether SLBs exhibit a sustainability premium—like green bonds’ “greenium”—and how SLB-specific features like the penalty

²Particularly by setting ambitious and science-based performance targets, setting sufficiently high penalties and issuing SLBs with no embedded call options to minimize the period in which the coupon step-up has to be paid issuers foster the credibility of SLBs.

³<https://www.environmental-finance.com/content/analysis/slbs-at-inflection-point-in-2023-as-sustainable-bond-market-rebounds.html>

scheme might affect the premium. The paper aims to fill a significant research gap by providing a comprehensive analysis of SLB-pricing behavior in both primary and secondary markets. Understanding the pricing dynamics of SLBs is critical for both issuers that have a high need for financing due to the requirements of the green transformation to a low-emission economy and therefore seek to optimize financing costs, and investors, who aim to balance the financing of firms with a credible commitment toward combating climate change with returns.

To the best of my knowledge, no other study has systematically compared SLB yields to conventional bonds from the same issuer across both the primary and secondary markets. This study also contributes to the broader discussion of whether sustainable assets, such as SLBs, exhibit a premium (i.e., trade at higher prices and lower yields) due to investors' taste for such assets, which may benefit issuers by lowering the cost of debt (Zerbib, 2019; Bachelet et al., 2019; Hachenberg and Schiereck, 2018). Additionally, this study adds to the discussion about determinants of yield differentials between sustainable and conventional assets (Bachelet et al., 2019; Kapraun et al., 2021; Larcker and Watts, 2020) and which SLB features might affect the pricing differentials in the cross-section (Kölbel and Lambillon, 2022; Erlandsson and Mielnik, 2022). Finally, the study is particularly timely given the rise in greenwashing concerns in the SLB market. Several contributions (Liberatore, 2021; Haq and Doumbia, 2022; Reznick et al., 2022) blame SLBs for being embedded with weak penalty structures, sustainability targets that are too easy to achieve or early call options so that the SLB can be redeemed before the penalty mechanism materializes. To date, Kölbel and Lambillon (2022) offer the most comprehensive study of SLBs; however, their research is limited to yield comparisons at the issuance stage (primary market). This paper goes further by extending the analysis to both primary and secondary markets. Theoretically, the analysis is based on Pedersen et al. (2021) and Pastor et al. (2021) developing ESG-adjusted asset pricing models and contribute to the debate over whether investors derive utility from sustainable investments and hence would be willing to pay higher security prices, i.e., accept lower returns. Given the flexibility and potential of SLBs to incentivize company-wide sustainability, expanding the literature to SLBs is crucial for practical implications in sustainable finance. This raises important questions in terms of how SLBs are priced and how SLB-specific features such as the penalty structure might impact the premium, further justifying the need for empirical research.

First, a primary market analysis is applied by fitting yield curves with the Nelson–Siegel–Svensson method (NSS) to construct yield curves for conventional bonds issued by the same company. Afterward, the SLB yield is overlaid, to examine whether the SLB priced below (would imply a sustainability premium) in line or above (would imply that SLBs

trade at higher yields and carry higher cost of debt for the issuer) its yield curve. Moreover, the SLB pricing in the secondary market is investigated by applying a fixed-effects panel regression which compares the yields of SLBs and a matched synthetic bond to investigate whether a potential sustainability premium would persist on the secondary market. Finally, the features that may drive yield differentials between the two bond types are examined.

The results provide several empirical findings. First, I provide an overview of the nascent SLB market, its promising framework and some structural and financial characteristics making this fixed income instrument prone to greenwashing risks. Empirically, I show that SLBs trade at a sustainability premium on the primary market which implies that issuers benefit from lower cost of capital and investors accept lower yields for holding a sustainability-linked asset. The premium of 4.68 basis points on average declines to 3 basis points when moving to the secondary market. Moreover, the premium is volatile over time and vanishes during the second half of 2022. Finally, cross-sectionally, there are differences regarding the premia with some SLBs exhibit higher yields compared to conventional bonds. Companies with the highest ESG score and companies that follow science-based targets priced tighter, i.e., those can expect lower cost of debt. In contrast, the cumulative size of the step-up in relation to the coupon of the bond is not a significant driver of the SLB premium, implying that this optional step-up is not a primary driver of SLB pricing. The remainder of the paper is structured as follows: Section “Related literature and hypotheses” reviews the related literature and posits hypotheses. Section “The sustainability-linked bond market” provides a market overview. Section “Data selection and methodology” highlights the sample selection process and the applied methodologies for the empirical part in section “Empirical results”. Section “Robustness” provides robustness tests. Finally, sections “Discussion” and “Conclusion” discuss the findings and conclude.

2.2 Related literature and hypotheses

The academic research so far primarily focused on regular green bonds, because of their historical dominance in terms of issuance volume. Leading contributions in the field mainly provided mixed evidence whether green bonds trade at a “greenium” implying lower yields for green bonds relative to conventional bond twins (Zerbib, 2019; Baker et al., 2018; Hachenberg and Schiereck, 2018; Gianfrate and Peri, 2019) or, in contrast, either at higher yields as reported in Karpf and Mandel (2018) and Bachelet et al. (2019) or at no difference (Larcker and Watts, 2020; Flammer, 2021). The mixed evidence is presumably attributable to different time periods, issuer types, markets and empirical approaches.

For example, some studies apply a matching approach to find a green bond’s “twin” and afterward regress its yield spread on remaining, not exactly matched explanatory variables (Zerbib, 2019; Bachelet et al., 2019), while other studies, instead of filtering out most of the conventional bonds through a matching procedure, regress the bond yields on a set of controls and a green dummy variable, which is the effect of being green on the bond yield spread (Baker et al., 2018; Fatica et al., 2021). A recent study by Kapraun et al. (2021)—equipped with the largest dataset to date—concludes that investors became skeptical about the environmental impact of green bonds and those only exhibit a green bond premium (of -4 bps), if they are externally certified as well as having a high sustainable reputation. Overall, the mixed findings on greenium in green bonds raise questions about whether SLBs, despite their structural differences, might exhibit a similar sustainability premium. Accordingly, this study’s first hypothesis is:

- 1. SLBs exhibit a sustainability premium in both primary and secondary bond markets, similar to the greenium concept in green bonds.**

In contrast to the above reviewed literature on green bonds research on SLB bonds is scarce. Most of the existing literature is qualitative, discussing the mechanism of SLBs and how SLBs could overcome the greenwashing concerns GSS bonds are confronted with (Vulturius et al., 2022; Giraldez and Fontana, 2022; Maino, 2022). The few empirical studies are as follows: Liberadzki et al. (2021) find that the SLB issued by the British grocery and retailer Tesco priced lower than conventional bonds issued by comparable firms such as Carrefour and Metro during the first half of 2021 even under the coupon step-up scenario. However, they match bonds with large differential in maturity. Kölbel and Lambillon (2022) find that SLBs price 29.2 bps lower than matched conventional bonds of the same issuer at issuance date on the primary market. Since the average step-up in their sample is 26.6 bps, issuers would benefit from a sustainability premium, even if they do not achieve their predefined performance target. They conclude SLBs are a “free lunch” to issuers. Berrada et al. (2022) create a conceptual framework that examines under which conditions SLBs incentivize company managers to exert effort, which will occur when the penalty saving is higher than the monetary cost of exerting effort to achieve the performance target. Moreover, environmental-concerned investors that observe manager’s effort, derive a benefit from the improved performance and are willing to pay higher bond prices. Therefore, companies with a more credible ESG strategy could exhibit higher SLB premia as hypothesis 2 states:

2. Building on findings that issuer characteristics, such as ESG scores, influence bond pricing, issuer-specific characteristics are associated with an SLB premium.

While SLBs hold potential to address certain limitations of green bonds, empirical research on their pricing remains limited, especially in comparison with green bonds. As most studies focus on the primary market, they may not account for changing market conditions, which could affect SLB pricing over time. For instance, Kölbel and Lambillon (2022) only compare primary market issuance yields, while Berrada et al. (2022) explore SLB mispricing by setting upper and lower pricing bounds but do not examine yield behavior over a longer time span. The role of SLB-specific features, particularly penalty mechanisms, is also an area needing further exploration. Existing research suggests that issuers could benefit from lower costs of capital by setting ambitious sustainability targets, substantial coupon step-ups and longer periods to achieve these targets (Erlandsson and Mielnik, 2022). These authors argue that greenium in SLBs should account for the option value of the step-up clause, as it can create optionality to receive higher payments if targets are missed. Therefore, hypothesis 3 posits:

3. Given the role of penalty structures in SLBs, its specific features, such as penalty magnitude for missed sustainability targets, affect the premium.

Despite the rapid growth and importance of SLBs, significant gaps remain in understanding their pricing, particularly in secondary markets where changing conditions could impact yields. Given the structural differences between SLBs and green bonds, it is essential to investigate whether SLBs demonstrate similar premium and which unique factors might drive their pricing dynamics.

2.3 The sustainability-linked bond market

The inaugural bond was launched by Italian utility Enel S.p.A. in September 2019. The single tranche, totaling \$1.5 billion, maturing in September 2024 and paying a rate of 2.65% is subject to the percentage of installed capacity in renewable energy. If a 55% of installed renewable generation capacity (as a share of total consolidated installed capacity) had not been reached until December 31st, 2021, the coupon would have stepped up by 25 bps to 2.9% p.a. until the bonds' expiry date. In 2021, the performance target has been successfully reached; therefore, the rate remained at a 2.65% p.a. level.⁴ According

⁴Enel reported to have reached 57.5% of installed new renewable generation capacity by the end of 2021.

to Enel, the transaction was successful, enabling the Italian energy company to obtain a financial advantage equal to 20 bps compared to a conventional bond issuance (Enel, 2019).⁵

In the wake of the publication of the ICMA guidelines in June 2020, five core components were established to ensure a certain standard including: selection of a Key Performance Indicator, calibration of a sustainability performance target, definition of the varying bond characteristics (i.e., most commonly the magnitude of the coupon step-up), reporting standards and third-party verification. The prior stagnant issue volume of SLBs skyrocketed. In September 2020, the Brazilian pulp and paper company Suzano issued the second USD \$750 million SLB.

Figure 2.1: SLB Issuance Volume

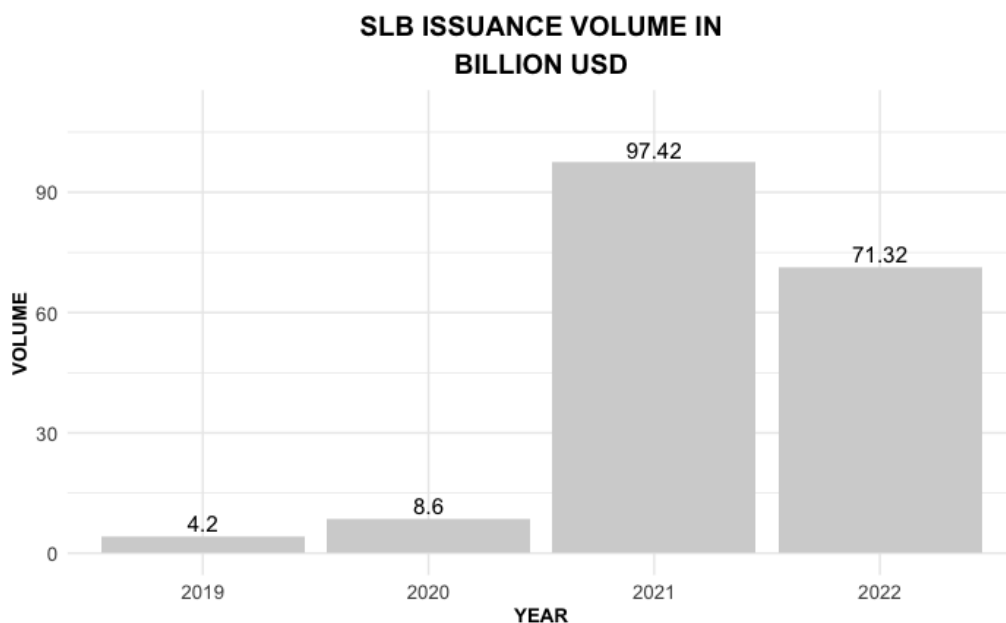


Figure 2.1: SLB Issuance Volume in Billion USD. This figure plots the amount of issued SLBs in billion USD between 2019 and 2022 according to data from Refinitiv.

As Fig. 2.1 shows, the last quarter in 2020 saw an issuance volume of \$8 billion followed by a soaring growth in 2021. As for all (green) debt assets, the issuances in 2022 declined, affected by rising interest rates, increased economic uncertainty, a worsening risk perception and the war in the Ukraine. Appendix Fig. A.1.1 shows that half of SLBs are denominated in Euro, followed by the US dollar. Together, the two currencies account for 84% of the issued volume. Next, Appendix A.1.2 plots the issuance volume across sectors

⁵See Enel's press release: <https://www.enel.com/content/dam/enel-common/press/en/2019-September/SDG.pdf>

in percent. Strikingly, carbon intensive “hard to abate sectors” like utilities, industrials or basic materials that are sometimes not compatible with the green bond standards (Maino, 2022), represent a high portion of SLB issuance. About half of the bond’s performance indicators are related to a greenhouse gas emission target as Fig. A.1.3 shows. Among those, over 80% focus on scope 1 and scope 2 emissions,⁶ whereas type 3 emissions, which are harder to measure but often representing most of a company’s emissions,⁷ are rarely included. Emission-related KPIs offer the advantage of being more easily aligned with science-based scenarios, and some issuers have previously reported such data.

Since the issuance of SLBs is based on voluntary guidelines and principles established by the ICMA—leaving room for different interpretations—and no public authority sets a legal framework that monitors the issuance, SLBs could be prone to the risk of greenwashing primarily due to a small size of the (cumulative) coupon step-up that is not material, callable features to redeem the SLB before or shortly after the step-up materializes or unambitious performance targets that are achieved easily by the issuer. Figure A.1.4 plots the size of the coupon step-ups. The figures indicate that more than 50% of the SLBs are embedded with 25 bps penalty per annum either solely or aggregated if a bond carries more than one KPI. Regardless of the issuers rating its size or its coupon-rate, it is common practice to set the fee to 25 bps per annum.⁸ In summary, SLB have emerged as a promising instrument for sustainable finance, offering flexibility and financial incentives for issuers to achieve the statted performance targets. However, the market could be prone to greenwashing, as issuers choose the targets independently and set the penalty.

2.4 Data selection and methodology

The next sections focus on the final sample selection process and the applied methodologies that investigate the pricing of SLBs on the primary and secondary bond markets.

⁶The greenhouse gas protocol differentiates between different scopes of emissions. Scope 1 emissions are direct emissions a company causes during its production process. Scope 2 emissions are indirect emissions from the generation of purchased electricity, heat or steam. Scope 3 emissions are consequences of a company’s indirect activities in its value chain.

⁷According to Deloitte, Scope 3 is nearly always the biggest one and accounts for more than 70% of firms’ carbon footprint. See: <https://www2.deloitte.com/uk/en/focus/climate-change/zero-in-on-scope-1-2-and-3-emissions.html>

⁸Step-ups make up approximately 75% of the penalization scheme. Besides step-ups, the other common financial incentives associated with KPIs are coupon step-downs, redemption premia where the issuer pays a predetermined premium on the redemption price at maturity, donations to foundations or organizations of the issuer’s choice, early redemption where the bond is redeemed earlier at a predefined price and the purchase of carbon credits proportionate to the principal amount.

2.4.1 Sample Selection

Most of the data originates from Refinitiv’s ESG Bond Guide Database, which provides static GSS and SLB bonds, including size, maturity, issuance day, seniority and yield at issuance. Since the issuance of the inaugural SLB bond in 2019, Refinitiv has listed 526 SLBs as of the reporting date December 31st, 2022. Secondly, Refinitiv Eikon’s bond viewer app displays SLB terms, for instance, the KPI description, the magnitude of the coupon step-up, or the coupon payment dates. Since the SLB details are partly not yet comprehensive, terms were also collected manually, based on company press releases, investor relations, the offering memorandum and bond prospectuses. Additionally, the bond viewer app provides the debt structure of the issuer including all other active conventional bonds trading on the debt market and gives access to pricing and yield data. I downloaded the time series data of all issuers’ active bonds since the issuance day of the SLB until September 30th, 2022. Time series data includes bid and ask yields, yield to maturity, swap spreads, ask and bid prices, modified duration and the remaining time to redemption. From the initial 526 bonds, 76 bonds were dropped that exhibit a bifurcated structure.⁹ Secondly, 70 bonds with a varying coupon-type and 109 bonds that have either issued no other or a single bond are left out. Refinitiv Eikon lacks continuous yield and pricing data for some Chinese issuers, so those are also not considered. Additionally, only SLBs that have been issued before June 30th, 2022 are included within the sample and all bonds that have a callable feature are excluded because they could affect the pricing. Following Berrada et al. (2022), I keep bonds with a clean-up call option (where the bond can be called within the last three months of maturity) and with a make-whole callable feature (redeeming the bond is associated with higher costs for the company). Table 2.1 shows the sample selection procedure in more detail. To ensure comparability between SLBs and conventional bonds, a matching approach was applied based on specific criteria such as issuer, currency, coupon structure and credit rating. These conditions were essential in identifying comparable bonds for the final sample of 45 SLBs.

⁹152 SLBs are issued in a bifurcated structure having both a 144A offering, where the securities primary offered to US investors and a RegulationS offering, that covers an investor base outside the US. It is common for companies to issue both 144A and RegulationS securities. Refinitiv lists both the RegS and the 144A portion of the bond within its database, but to avoid double-counting the totals of the RegS offering type are not included and counted a second time.

Table 2.1: Final sample

Sample reduction	Number of SLBs
Initial sample	526
Less issued after June 30th, 2022	−89
Less bonds with both RegS and 144A offering	−76
Less floating coupon structure	−56
Less Chinese issuers/missing pricing data	−63
Less no CB	−56
Less 1 or 2 CB	−53
Less maturity matching	−35
Less other matching criteria	−53
Sample size	45

Table 2.1 summarizes the selection process, showing the final sample of 45 SLBs after the exclusions.

2.4.2 Methodology for Primary Market Analysis

The primary goal of the analysis is to determine whether SLBs exhibit a sustainability premium on the issuance day by comparing their yields to those of matched conventional bonds. This is done by applying the Nelson–Siegel–Svensson (NSS) method to construct yield curves for each issuer and overlaying the SLB’s yield to assess its relative positioning. In the first step, the presence of yield differentials between SLBs and matched conventional bonds—based on the issuer, coupon structure, currency and rating structure—is investigated on the pricing date of the SLB, where its yield, coupon and price are determined subsequently to the initial price talks, the book-building process and the allocation to investors. The SLB’s yield at issuance representing the yield the investor receives if the bond is held till maturity and performance targets are met (and the penalty mechanism does not materialize)¹⁰ is compared to the yield to maturity of conventional bonds already trading in the secondary market. The comparison allows to identify if SLBs are priced at lower yields. Therefore, the method of the Climate Bond Initiative (CBI 2017) is extended by applying the Nelson–Siegel–Svensson (NSS) method (Nelson and Siegel, 1987; Svensson, 1994). Typically, central banks estimate sovereign yield curves to obtain an empirical representation of the term structure of interest rates, serving as a key reference point for many other markets (Andersen, 2018). Appendix A.3 discusses the NSS and its application in more detail. The NSS method infers (theoretical) yields over the bonds’ remaining time to maturity spectrum visualized by fitting a yield

¹⁰It is industry practice to quote SLB yields without considering the potential (coupon) penalty (Berrada et al., 2022). All the collected SLB data from Refinitiv are quoted without the possible step-up.

curve for each of the 45 SLB-bond issuers on SLB’s pricing day. Afterward, the yield of the SLB is overlaid to determine whether its yield at issuance is below, in line or above its curve. If an SLB bond is below its yield curve it suggests a sustainability premium, where investors receive a lower yield, and issuers face lower cost of debt as they would have expected to receive if they would had held (issued) a conventional bond which is interpreted as evidence for sustainability premium investors pay. This approach offering a new perspective compared to the traditional green bond literature, which typically regress a panel of issuance yields for green and conventional bonds on a green dummy variable along with issuer and bond-specific data (Kapraun et al., 2021; Baker et al., 2018; Fatica et al., 2021).

2.4.3 Methodology for Secondary Market Analysis

To analyze the yield differentials between SLBs and conventional bonds on the secondary market subsequently, a matching approach was applied as in Zerbib (2019), Bachelet et al. (2019), Kapraun et al. (2021), Larcker and Watts (2020), Flammer (2021), or Gianfrate and Peri (2019). Unlike traditional regression methods, regressing the bond yields on their characteristics and a “green” dummy variable for the sustainable label, a matched-pairs approach is applied that allows for isolating the “sustainability” label effect directly by controlling for bond characteristics that impact both SLBs and conventional bonds similarly. As noted by Zerbib (2019) and Bachelet et al. (2019), matching ESG-related bonds with (synthetic) conventional bonds is more appropriate for distinguishing yield differentials because it minimizes the noise that could result from unobserved differences between bond characteristics, which are not captured by dummy variables. It has become a widely accepted method in the green bond literature for measuring the pricing effect of sustainability labels (Kapraun et al., 2021). Therefore, a synthetic bond is created by selecting two conventional bonds with the closest maturity, spanning an interval of ± 3 years to the SLB again having the same characteristics (same issuer, currency, seniority (payment rank), callable or bullet structure, rating) except the sustainability label. On each respective day of the remaining SLB’s tenor, the ask yield of the synthetic bond is linearly inter- or extrapolated to account for maturity differences. The inferred theoretical yields of the synthetic bond match the SLB’s residual maturity. Beyond the matching approach and the creation of the synthetic bond, liquidity differentials remain a potential driver of ask yield differentials. Therefore, the ask yield differential of the bond pairs $\Delta y_{i,t}$ is regressed on the bond pairs bid–ask spread via fixed-effects panel regression following the methodology used by Zerbib (2019), Kapraun et al. (2021), Bachelet et al. (2019), to extract the sustainable effect as:

$$\Delta y_{i,t} = p_i + \Delta Liquidity_{i,t} + \varepsilon_{i,t} \quad (2.1)$$

with p_i being the fixed effect that captures the time-invariant unobserved “sustainable” effect for each issuer. Hence, p_i is the residual difference between a SLB and the synthetic conventional bond that is attributable to the the sustainable label of the bond after controlling for liquidity differences. To measure liquidity spreads $\Delta Liquidity_{i,t}$, bid–ask spreads are used, one of the most widespread proxies for bond liquidity (Fong et al., 2017).

Finally, a cross-sectional regression is conducted to investigate the determinants of the varying sustainability premium across issuers. Specifically, the sustainability fixed effect p_i of each of the 45 issuers is regressed on a set of issuer-level control variables as follows:

$$p_i = \alpha_0 + \text{Controls}_i + \varepsilon_i \quad (2.2)$$

Control variables include quantitative variables, i.e., the maturity, the issued amount and qualitative variables: rating and the currency. Rating is a scaled variable which is assigned in ascending order, while currency is a dummy variable equal to 1 if the SLB is issued in USD. Moreover, SLB-specific controls in terms of the coupon step-up and the commitment to science-based targets are added.

2.5 Empirical results

The next section presents the results of the yield curve fitting for the primary market in 2.5.1 and the results of the fixed-effect panel regression after applying a matching procedure.

2.5.1 Primary market results

Appendix A4 plots the estimated yield curves for each of the 45 SLB issuers (see figure A.4.1). The blue dots represent the conventional bonds’ yield to maturity—given its remaining lifetime—while the green dots show the yield at issuance of the SLB. Overall, the yield curves exhibit the typical upward slope, with higher yields for longer-term debt. Besides, the SLB yield and the inferred conventional bond yield differ from each other.

While some bonds (Snam, A2A, Carrefour, Novartis) exhibit a new issue concession, implying that the SLBs trade above the yield curve (to the benefit of investors), most of the SLBs trade at slightly (e.g., Deere, Fuyo) or clearly lower yields (e.g., Suzano, Ana Holdings, General Mills). Overall, this confirms the first part of hypothesis 1 that SLBs trade at a premium on the primary market. Moreover, this finding is consistent with Baker et al. (2018), Fatica et al. (2021) or Kapraun et al. (2021) who find that green municipal and green corporate bonds trade at a “greenium” at issuance implying lower yields compared to conventional bonds.

The difference in the mean of yields between is -4.68 basis points, which implies that issuers on average can expect lower cost of capital if they issue SLBs, provided that the penalty does not materialize prospectively. This is consistent with Berrada et al. (2022), concluding that 20% of the SLBs are overpriced (to the benefit of the issuer and its shareholders) and with Kölbel and Lambillon (2022), although the yield difference is much lower than theirs. The p-value of a paired two-sided t-test and a nonparametric Wilcoxon test, provided in Table 2.2, confirm that the yields are significantly different from each other.

Table 2.2: Paired t -test and Wilcoxon Test Results for SLB vs. Conventional Bonds

Statistic	Value (bps)
Yield SLB	141.960
Yield Conventional Bond	146.640
Yield Differential	-4.680
p -value (t -test)	0.010
p -value (Wilcoxon test)	0.060

Do SLBs trade at lower yields on the primary market? Table 2.2 reports the mean yields and yield differential, along with the p-values of the paired t-test and Wilcoxon test comparing SLB and conventional bond yields at issuance, as described in section “Methodology for primary market analysis.”

Finally, the distribution of yield differences is plotted in Fig. 2.2 representing the kernel density for the 45 bond pairs in basis points.

Figure 2.2: Distribution of Yield Differentials at Issuance

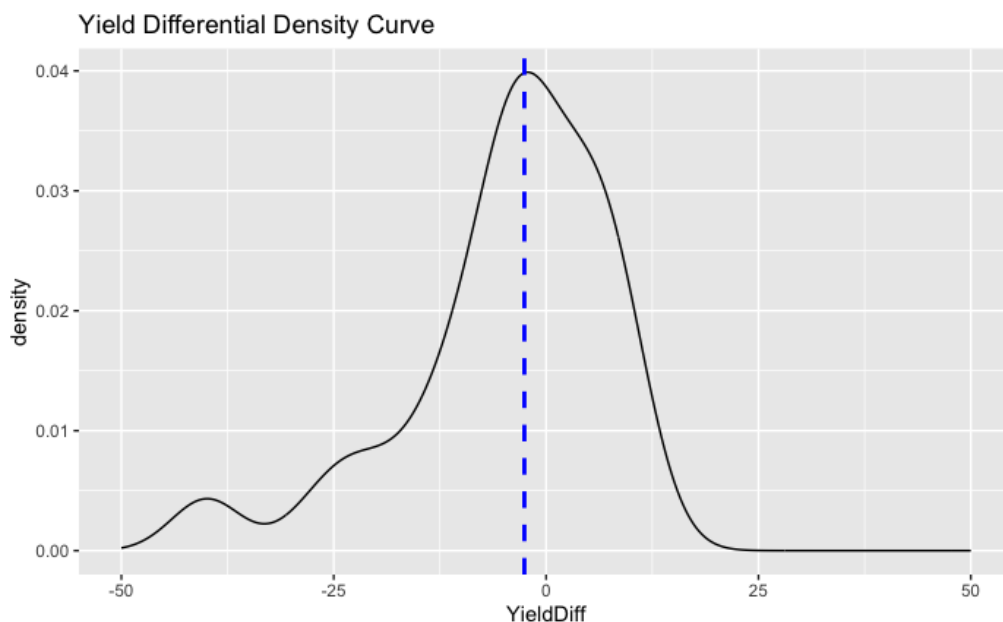


Figure 2.2: Density curve of yield differentials in basis points. This figure plots the density of the SLB and conventional bond yield differential across 45 SLBs. The SLB yield is the yield at issuance, while the conventional bond's yield is the estimated NSS yield at the same maturity by fitting a yield curve. The x-axis plots the yield differential, whereby a negative value is an indication that a premium exists. The blue dashed line is the median of the yield difference.

A large mass is centered slightly left from zero yield differential, skewed to the left with thin tails indicating that SLBs trade at lower yields and some exhibit particularly large differentials. The blue dashed line plots the median of the distribution which is also negative (-2.56 basis points).

2.5.2 Secondary market results

The primary market analysis examines yield differentials solely on the issuance day which can be influenced by a gap between debt supply and demand (for instance, rate hikes could occur on the issuance day). Table 2.3 reports summary statistics. The average SLB yield in the sample is 2.10 % (210 bps) slightly below the synthetic bond yield which is 2.12%. Moreover, the synthetic bond is more volatile than the SLB and the bid-ask spread between the bond pairs is centered around zero with a low standard deviation.

Table 2.3: Descriptive Statistics of Matched Bond Pairs

Statistic	N	Mean	St. Dev.	Min	Median	Max
Yield Spread	12,184	−0.02	0.14	−1.03	−0.01	0.99
Yield SLB	12,183	2.10	1.76	−0.44	1.87	7.97
Yield synthetic	12,184	2.12	1.78	−0.29	1.86	8.22
Liquidity spread	12,184	−0.01	0.18	−0.60	−0.001	0.74
Remaining maturity SLB	12,184	6.93	2.26	1.70	6.75	12.41
Remaining maturity CB1	12,184	5.59	1.68	1.65	5.82	9.44
Remaining maturity CB2	12,184	7.12	2.02	2.32	7.44	12.64

Table 2.3 shows descriptive statistics of matched bond pairs. Yield spread is the difference between the yields of the SLB bond and the two matched synthetic bonds. Yield SLB is the yield of the sustainability-linked bond. Yield synthetic is the linearly inter- or extrapolated conventional bond yield of the two closest conventional bonds at the same residual maturity as the SLB. The liquidity spread is the difference in bid–ask spreads between the SLB and the synthetic bond. The last three rows contain the distribution of maturities.

Before estimating the yield differentials, a bunch of statistical tests is applied. Appendix Table A.2.1. lists the results. A Hausman test indicates that the fixed-effects regressor is more efficient than the random effects estimator. Since the Breusch–Pagan test implies that the error variances are heteroscedastic equation (2.1) is estimated with robust standard errors. Moreover, Beck–Katz robust estimation is used to address the presence of serial correlation and Driscoll–Kraay standard errors both correct for serial correlation and cross-sectional dependence.

Next, table 2.4 shows the result of the fixed-effects regression.

Table 2.4: Fixed-Effects Regression

	Dependent Variable: Yield Spread			
	Within	Robust Std.Err.	Beck-Katz	Driscoll-Kraay
	(1)	(2)	(3)	(4)
Liquidity Differential	−0.290*** (0.012)	−0.290 (0.192)	−0.290** (0.121)	−0.290*** (0.046)
Observations	12,183	12,183	12,183	12,183
R ²	0.046	0.046	0.046	0.046
Adjusted R ²	0.042	0.042	0.042	0.042

*This table shows the result of the regression $\Delta y_{i,t} = p_i + \Delta Liquidity_{i,t} + \varepsilon_{i,t}$. The dependent variable $\Delta y_{i,t}$ subtracts the ask yields of the SLB from the matched synthetic bond. $\Delta Liquidity_{i,t}$ is the difference in bid–ask spreads between SLBs and the synthetic bond. The sample comprises a daily unbalanced panel with the earliest information on October 15th, 2019 and the latest on September 30th, 2022. *** implies significance at the 1% level, while ** implies significance at the 5% level.*

First, the bid–ask spread significantly determines the ask yield differential between the SLB and conventional bond of the respective issuer. A 1-bps increase in the bid–ask spread differential decreases the yield spread differential by 0.29 bps. Intuitively, one would have expected a positive relationship, because higher bid–ask spreads (higher illiquidity of sustainable assets) should offer higher returns of the SLBs, but the finding is consistent with the green bond literature (Bachelet et al., 2019; Zerbib, 2019; Kapraun et al., 2021). The negative relationship remains significant when the standard errors are adjusted with Beck–Katz and Driscoll and Kraay robust standard errors to account for serial correlation and cross-sectional dependence, respectively.

More importantly, Table 2.5 shows the distribution of the estimated fixed effects p_i (the differences in yields that is attributable to the sustainability feature of a bond) having a mean of nearly - 3 bps (-0.03%) and a median of - 2.12 bps, implying that SLBs trade tighter than their conventional bond-twins.

Table 2.5: Distribution of the Sustainable Premium

Statistic	N	Mean	St. Dev.	Min	Median	Max
p_i (Fixed Effect)	45	-0.030	0.088	-0.336	-0.021	0.159

This table shows the distribution of the estimated SLB premium. The premium is defined as the fixed effect p_i of the regression $\Delta y_{i,t} = p_i + \Delta Liquidity_{i,t} + \varepsilon_{i,t}$.

On average, issuers can expect lower cost of capital when they issue SLBs, and investors pay a small premium to hold SLBs. Although the premium is slightly smaller than on the primary market it remains significant. Again, this finding confirms hypothesis 1 and is consistent with studies that find a small greenium in the secondary market (Zerbib, 2019; Kapraun et al., 2021). Table 2.5 further indicates that the estimated sustainability premium is not stable across the sample, but ranges from - 33.6 bps to 15.9 bps. Finally, Table A.2.2 in the appendix compares the estimates of the premia for all the 45 issuers on both the primary market and on the secondary market. Overall, the estimated premia often differ slightly from each other and are low; however, some SLBs that exhibited a sustainable premium on the primary market, (i.e., Deere, CPI, Analog Device, NWD, Sembcorp) traded at higher yield on average thereafter.

2.5.3 Determinants of the premium

To test hypotheses 2 and 3, a cross-sectional regression specified by equation (2.2) was conducted by regressing the fixed effects (i.e., the yield differential attributable to the sustainable label) on a set of controls, including the ESG score or the magnitude of the penalty step-up. The first specification of Table 2.6 implies that neither the maturity nor the issued amount significantly determines the premia. Also, a higher rating is not associated with a sustainability premium. On the other hand, SLBs denoted in USD seem to have slightly higher premia, although the effect does not remain significant.

In column 2, additional controls are added, that specify attributes of the SLBs. SBTi is a dummy variable equal to 1, if the issuer has set targets aligned with science-based scenarios.¹¹ Although columns 2 and 3 find lower yields of -3.9 bps and -2.6 bps for SLBs that have been issued in accordance with science-based scenarios, the effect turns out to be insignificant when the step-up penalty is added in column 3. Following Kapraun et al. (2021), a top ESG- Rating above 85 is included in columns 2 and 3. Issuers with a high ESG-score benefit from a premium as of 7.7 to 10.2 bps. This result is consistent

¹¹Science-based targets provide a trajectory for companies how emissions must be reduced to meet the goals of the Paris Agreement a legally binding international treaty that aims to hold the increase in the global average temperature to well below 2°C above preindustrial levels.

with Hartzmark and Sussman (2019) and Kapraun et al. (2021): Investors are attracted by extreme ratings and apply a top-down approach which results in the selection of the assets of ESG leaders. This provides partial support for hypothesis 2, which posited that issuer-specific variables like the ESG score could influence the sustainability premium.

Specification 3 only considers those SLBs which have a coupon step-up as penalization mechanism resulting in 32 observations left. The step-up control in specification 3 relates the cumulative step-up amount of the penalty to the coupon of the bond (how much of the annually original coupon must be additionally paid?). The sustainability premium is not significantly driven by the penalty structure of the SLB. A higher cumulative coupon step-up—which materializes, if the future SPT will not be achieved—does not have the expected negative sign and is not associated with a SLB-yield premium. Therefore, hypothesis 3, which anticipated that SLB-specific features—such as the magnitude of the penalty—would affect the premium, is not confirmed, indicating that the structure of the penalty mechanism may not be as critical to investors as previously thought.

Table 2.6: Determinants of the Premia

	<i>Dependent Variable: Green Premium (Fixed Effects)</i>		
	(1)	(2)	(3)
Maturity	−0.002 (0.005)	−0.003 (0.004)	−0.006 (0.005)
Log(Amount)	0.009 (0.017)	0.023 (0.016)	−0.015 (0.023)
Rating	−0.001 (0.007)	0.002 (0.009)	0.002 (0.007)
Currency USD	−0.067 (0.044)	−0.031 (0.037)	−0.003 (0.034)
SBTi		−0.039 (0.026)	−0.026 (0.024)
ESG		−0.077** (0.035)	−0.102*** (0.039)
Step-up Magnitude			0.046** (0.018)
Constant	−0.174 (0.436)	−0.434 (0.434)	0.296 (0.542)
Observations	45	43	32
R ²	0.102	0.286	0.448
Adjusted R ²	0.012	0.168	0.286
Residual Std. Error	0.088 (df = 40)	0.082 (df = 36)	0.084 (df = 24)
F Statistic	1.134 (df = 4; 40)	2.409** (df = 6; 36)	2.777** (df = 7; 24)

*This table explains the fixed effects defined as the premium p_i expressed in percentage by different characteristics. Maturity is the residual maturity of the SLB on September 30th, 2022, measured in years. Amount is the issuance size of the SLB in USD. Rating is scaled in ascending order. Currency is a dummy variable equal to 1 if the SLB is issued in USD. ESG is a dummy variable equal to 1 if the ESG score of the company is above 85. SBTi is a dummy for commitment to science-based targets. Step-up refers to the cumulative coupon step-up relative to the SLB coupon. Robust standard errors in parentheses. Significance codes are: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.*

2.6 Robustness

As a robustness, several econometric modifications are performed. First, it is examined whether the 3-bps secondary market sustainability premium is driven by lower risk of the

SLB. Therefore, equation 2.1 is modified by adding the annualized bond yield variance of the SLB and the synthetic CB computed ex post in a 10-day rolling window (as in Bachelet et al., 2019).

$$\Delta y_{i,t} = p_i + \Delta Liquidity_{i,t} + \Delta Volatility_{i,t} + \varepsilon_{i,t} \quad (2.3)$$

Appendix Table A.2.3 depicts the distribution of the SLB premium when the difference in variance is added to the fixed-effects regression. As expected, the ask yield differential is positively correlated with the volatility difference. The negative yield differential remains, but slightly drops to -2.4 bps. The persistence of a negative yield differential, despite adjusting for volatility, suggests that the SLB premium is not merely a risk premium. This implies that other factors, potentially related to the sustainable label, are more influential in driving the pricing differential. Secondly, instead of applying a matching approach, I run a regression that explains bond yields by common factors from bond literature. For each of the 45 SLBs, the closest CB of the same issuer is selected. The following model is estimated, in Appendix Table A.2.4:

$$Yield_{i,t} = \alpha_i + \beta SLB_i + \gamma X_{it} + \delta M_t + \varepsilon_{it} \quad (2.4)$$

$Yield_{i,t}$ are the ask yields of the SLB and the CB, respectively, observed from the first trading day on the secondary market until the 30th September 2022 and are regressed on a set of dummy variables α_i including currency, issuer, rating and sector fixed effects and the time-varying control variables bid-ask spread and a residual maturity $X_{i,t}$. Following Pietsch and Salakhova (2022), the second column of Table A.2.4 adds macro variables to the regression. The short 3-month treasury securities and the long 10-year treasuries are key factors in bond pricing, as well as the risk aversion of market participants proxied by the VIX. The main variable of interest is the SLB-dummy which equals 1 if the bond is an SLB and 0 otherwise. Consequently, the estimated beta is the yield differential attributable to the sustainable component of the bond, implying that SLBs trade at lower yield if beta is negative.

Model 1 adds time fixed effects to control for unobserved effects that are constant across issuers but vary over time, while the second model estimates equation 2.4. The OLS regression is estimated with robust standard errors to account for serial correlation and heteroscedasticity. Overall, SLBs trade at lower yields of around -2 basis points after controlling for the introduced effects above. This is highly consistent with the fixed-effects model, reinforcing the robustness of the premium. The control variables, such as

maturity and bid–ask spread, exhibit the expected signs.

Finally, it is examined how the yield differential evolves over time. Pietsch and Salakhova (2022) stress that the greenium is not constant but varies over time. The theoretical model of Pastor et al. (2021) shows that green assets can suddenly outperform, if investors are environmentally concerned and shift their investments toward “green” holdings. Therefore, equation (2.1) is estimated on a monthly subsample basis, starting from January 2022. Appendix Fig. A.1.5. plots the estimated sustainable premium for each month. The yield differential not only varies over time but becomes positive in July (nearly +3 bps). Additionally, the yield differential fluctuates over time, turning positive May and July 2022. This variation aligns with theories, suggesting that green or sustainable asset premiums are not static and can change in response to shifts in investor sentiment or broader market conditions. Such changes might reflect temporary market dynamics, like shifts in ESG investor sentiment or macroeconomic factors such as inflation or interest rate expectations.

2.7 Discussion

Overall, the empirical results must be considered carefully due to the small sample size that and the early stage of the SLB market but warrant a further discussion. The sustainability premia found in both the primary and the secondary align with existing theoretical work (i.e., Pedersen et al., 2021; Pastor et al., 2021) and empirical findings (i.e., Zerbib, 2019; Kapraun et al., 2021): investors pay higher prices (accept lower returns) for green assets reflected in a premium. The premia of -4.68 bps in the primary market and -3 bps in the secondary market indicate that investors might be willing to pay a small premium to support beneficial environmental projects aligned with the first hypothesis. However, contrary to green bonds, the premia do not necessarily imply that investors are willing to sacrifice return to hold green assets for nonpecuniary motives because they can expect a compensation if the issuer fails to achieve its sustainability performance target(s).¹² Further, the decaying premium on the secondary market and the time trend of the green premium imply that the SLB premia is not constant over time, lowered in 2022 and turned into a discount (higher yields) of +3 bps in July. This is consistent with critical voices denouncing the structural implementation of SLBs. The latest is by NGO Mighty Earth which has filed a complaint about the SLB of Brazilian meat producer JBS. Some ESG investors like Nuveen refused to invest in SLBs. The goals and

¹²To assess whether investors are prepared to sacrifice return, one must infer the probability that the coupon steps up. Erlandsson and Mielnik (2022) treat the step-up as a call option and apply the Black–Scholes–Merton model to extract the probability that the coupon steps up. The SLB yield could then be step-up adjusted and compared to the conventional bond yield.

targets could be “gamed to make them relatively easy to achieve.” Moreover, the current size of the coupon step-up is not enough of a penalty (Libertore, 2021). All this would lower the willingness to pay higher prices (accept lower yields) for SLBs, resulting in a decaying premium especially if issuer benefit from lower cost of debt without providing serious effort to climate change and no chance of financial penalty. Issuers with high ESG-scores benefit from a premium around 8 bps higher than those of ESG-laggards, confirming hypothesis 2, that issuer-specific characteristics like the ESG score can explain yield differentials partially. This finding is consistent with previous research, suggesting that companies with higher ESG performance benefit from lower cost of capital (i.e., Bauer and Hann, 2014) most likely because of a negative relation between ESG and risk (Krueger, 2015) due to better risk management and mitigation, and a positive relation between ESG and company’s future financial performance (Eccles et al., 2014; Flammer, 2021) through intangible asset creation. Strikingly, I find that the premium is not driven by the bonds’ financial penalty structure in the cross section, rejecting hypothesis 3. Theoretically, a higher potential coupon step-up should lead to higher bond prices and (and consequently lower SLB yields and higher SLB premia) reflecting potentially higher interest-payments. However, the findings seem to support the hypothesis that investors expect that the likelihood of receiving step-up payments might be close to zero reflecting investor skepticism toward the real enforceability of these penalties, as noted by Haq and Doumbia (2022). Issuers set targets, they are likely to achieve (Kölbel and Lambillon, 2022). Therefore, investors could perceive SLBs as long-term commitments and focus more on overall ESG performance and the company’s sustainability trajectory, rather than the specifics of the penalty structure.

2.8 Conclusion

The central innovation SLBs provide is that their financial characteristics can vary depending on whether a predefined sustainable performance target has been achieved. Typically, the coupon steps up 25 bps for the remaining lifetime of the bond if the target is missed. SLBs can be a promising instrument because they incentivize issuers to fulfill the targets, provided that the coupon step-up is material, and the targets are ambitious enough. The provided market overview showed the rapid development of the market especially in Europe. Most likely, SLBs carry a coupon step-up as penalty mechanism and the penalty is centered around 25 bps regardless of the issuers credit quality. This study provides insights into the early stage SLB market, highlighting the potential pricing differences between SLBs and conventional bonds. On average, SLBs trade at a premium, both on the primary market (-4.68 bps) and the secondary market (-3 bps), allowing issuers to benefit from lower capital costs. However, this premium decays over time, reflecting grow-

ing investor skepticism about the credibility of SLB targets and penalties. The penalty structures appear to lack the materiality necessary to significantly affect bond pricing, raising questions about the long-term viability of SLBs as a credible sustainable finance tool. While the potential drivers of the sustainability premium are difficult to assess due to the small sample size of the matched bond sample and the early stage of the market, first evidence suggests issuers having a better sustainable reputation (in terms of a higher ESG-Rating) and following science-based scenarios to benefit from a sustainability premium. This study holds important implications for both investors seeking to optimize financing costs while supporting sustainability, and policymakers aiming to design more effective frameworks that ensure the credibility of sustainability-linked financial instruments. Further research is essential to determine how SLB structural features — such as penalty magnitude and target ambition — translate into pricing behavior. Next, future studies could implement the probability that the coupon will step up by investigating the likelihood of that the performance targets will be achieved (missed) and how this translates into the pricing of SLBs (Erlandsson and Mielnik, 2022). Finally, understanding investor sentiment around SLBs, particularly in the face of potential greenwashing, would provide deeper insights into how this market may evolve.

Appendix A

A.1 Figures

Figure A.1.1: Currency Distribution

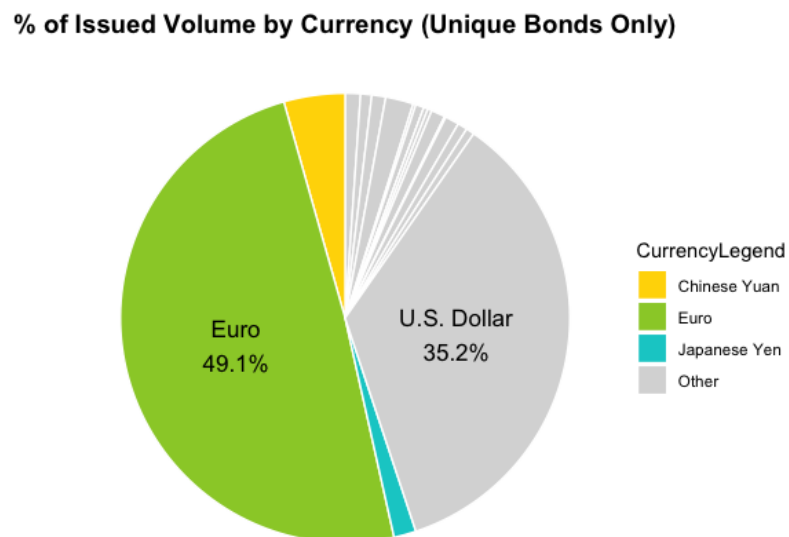


Figure A.1.1: Currency distribution. Refers to the distribution of currencies in % of issued volume. Eighty-six percent of total SLB issued amount are either denominated in EUR or USD.

Figure A.1.2: Issuance Across Sectors

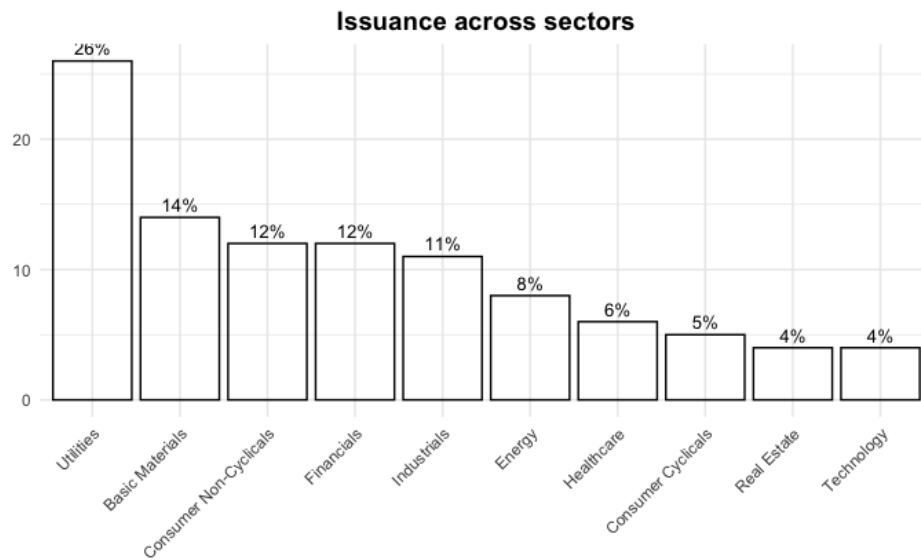


Figure A.1.2: Issuance across sectors. Shows the issuance volume across different sectors. Carbon-intensive sectors like utilities, basic materials or industrials have the highest proportion.

Figure A.1.3: KPI Distribution

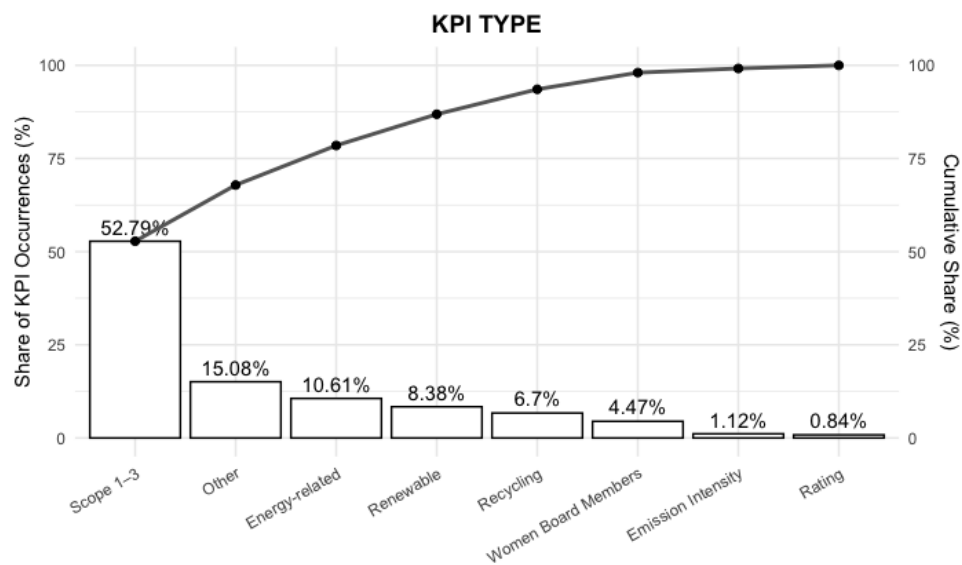


Figure A.1.3: KPI distribution. Clusters the KPI types into eight different upper groups. For instance, the Scope 1–3 group includes all KPIs related to emission reduction (total greenhouse gas reduction, reduction of CO₂ intensity, reduction of toxic gases).

Figure A.1.4: Coupon Step-Up

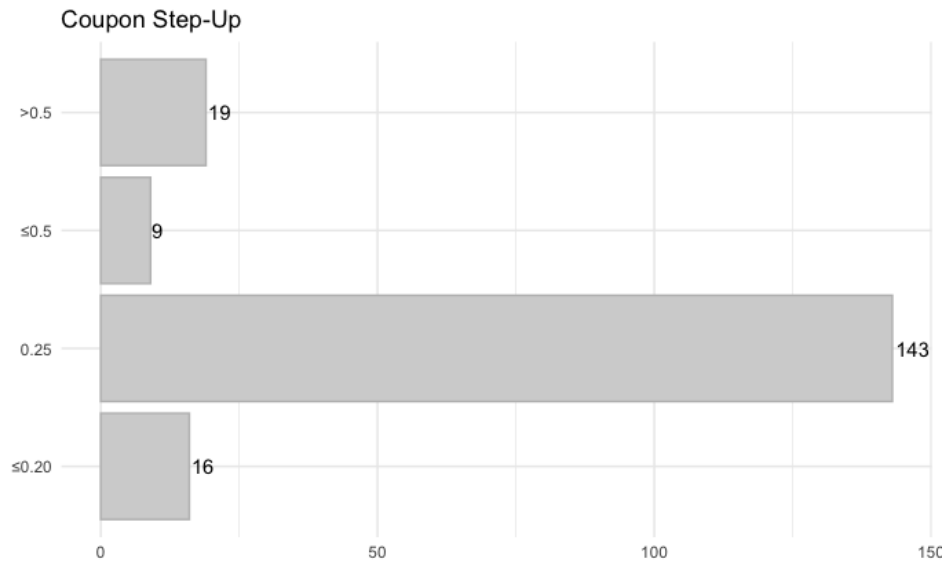


Figure A.1.4: Coupon step-up. Plots the magnitude of the coupon step-ups for all the SLBs that have a step-up penalty. Most commonly, the magnitude of the step-up consolidates at 25 bps.

Figure A.1.5: Estimated Secondary Market Premium Over Time

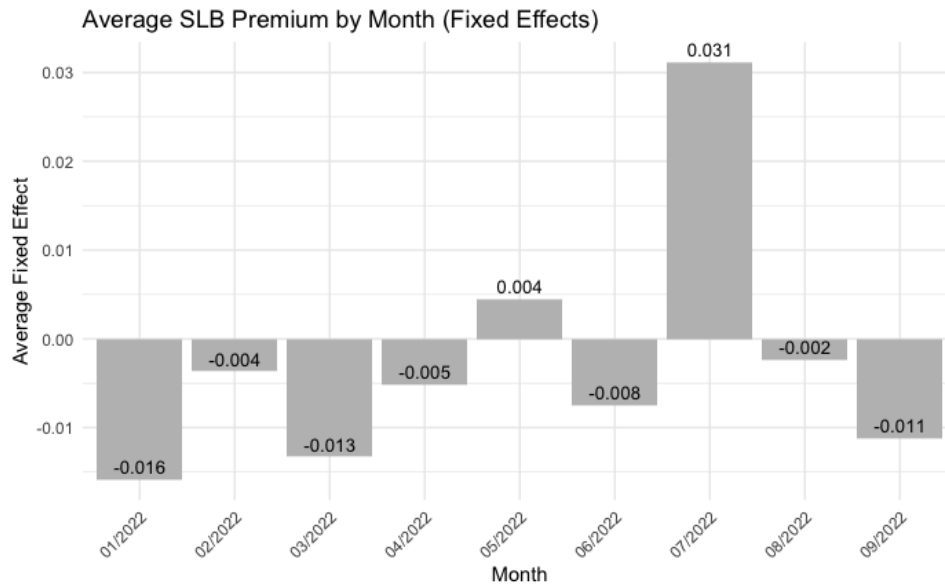


Figure A.1.5: Estimated Secondary Market Premium over time in %. Refers to a time trend in the sustainability premium. Instead of estimating the baseline equation $\Delta y_{i,t} = p_i + \Delta \text{Liquidity}_{i,t} + \varepsilon_{i,t}$ over all time periods, the sample is divided into monthly subsamples to measure the sustainability premium for each month. The estimated average fixed effect p_i (i.e., the sustainability premium) is plotted for each month from January 2022 to September 2022.

A.2 Tables

Table A.2.1: Diagnostic Tests for Panel Regression

Test	Statistic	p-value	Interpretation	Conclusion
F test for individual effects	134.15	0	Reject the null hypothesis that a model with no independent variables fits better	Presence of individual effects
Hausman test	8.08	0.0044	Reject the null hypothesis of no correlation between errors and regressors	Use of fixed effects
Breusch–Pagan test for heteroscedasticity	66.07	0	Reject the null hypothesis that the error variances are all equal	Presence of heteroscedasticity
Breusch–Godfrey/Wooldridge test for serial correlation	8429	0	Reject the null hypothesis of no autocorrelation between the residuals	Presence of serial correlation
Pesaran test for cross-sectional dependence	13.97	0	Reject the null hypothesis of no cross-sectional dependence	Presence of cross-sectional dependence

This table reports the results of various diagnostic tests conducted on the panel regression model to assess the suitability of fixed effects and the presence of heteroscedasticity, serial correlation, and cross-sectional dependence.

Table A.2.2: Estimated Premia on the Primary and Secondary Market

SLB	YieldDiff Primary (bps)	YieldDiff Secondary (bps)
A2A	4.340	8.647
AeonMall26	-23.760	-12.739
AeonMall27	-2.560	-3.025
AnaHoldings	-40.530	-5.947
Analog	-2.310	5.509
Axpo25	-8.660	-5.178
Axpo27	4.190	1.936
Carrefour26	11.430	7.026
Carrefour29	8.090	9.774
CPI	-5.790	3.753
Deere	-4.930	1.800
Enel24	-4.210	0.843
Enel26USD	-7.560	-9.187
Enel27	5.400	5.111
Enel28USD	0.520	-6.200
Eni	5.260	3.064
Fuyo	-2.290	3.233
GeneralMills	-10.730	-11.430
Helsingborg0.75	-20.070	-7.984
Helsingborg0.875	-22.870	-2.129
Holcim	-2.620	-1.703
HoclimHelvetia	-4.230	-1.409
Hulic	-11.520	3.252
Legrand	7.630	-9.556
LondonQadrant	1.070	-0.922
Novartis	6.000	6.692
NWD	-4.520	7.048
Obayashi	-11.250	-6.850
Optus	5.020	6.906
Pernod	2.490	-3.183
Repsol	1.260	15.854
S&P	9.180	-14.109
Sanofi	-0.460	-1.898
Sembcorp	-7.840	0.243
Sembcorp22	-1.950	-5.342

Table A.2.2 (continued)

SLB	YieldDiff Primary (bps)	YieldDiff Secondary (bps)
Snam29	10.040	-16.165
Snam34	7.910	-9.773
Suzano20	-27.670	-18.106
Suzano28	-16.000	-33.613
Suzano32	-39.410	-7.883
TDK26	-4.620	-4.751
TDK28	-1.080	-1.034
Telus	-3.860	-9.094
Toda	7.670	-12.531
Woolworth	-14.720	-2.817

This table shows the estimated premia on the primary and on the secondary market. The primary market estimation is the difference between the yield of the SLB at issuance and the yield curve estimated with the NSS method. A negative value implies a sustainability premium.

Table A.2.3: Fixed-effects Regression with Volatility Control

Statistic	N	Mean	St. Dev.	Min	Median	Max
p_i	45	-0.024	0.085	-0.327	-0.018	0.159

This table shows the distribution of the estimated SLB premium. The premium is defined as the fixed effect p_i of the regression $\Delta y_{i,t} = p_i + \Delta Liquidity_{i,t} + \Delta Volatility_{i,t} + \varepsilon_{i,t}$. Volatility is the 10-day rolling annualized volatility of the SLB and the synthetic bond calculated ex post.

Table A.2.4: Fixed-Effects Regression on Yield Differentials

Dependent Variable:	Yield	
	Model (1)	Model (2)
<i>Variables</i>		
factor(Green) Yes	−0.02*** (0.005)	−0.02*** (0.005)
Maturity	0.09*** (0.005)	0.03*** (0.004)
Bid-Ask Spread	0.13*** (0.009)	0.13*** (0.01)
VIX		0.03*** (0.0006)
Short Treasury		0.21*** (0.005)
Long Treasury		1.1*** (0.007)
<i>Fixed Effects</i>		
Issuer	Yes	Yes
Rating	Yes	Yes
Currency	Yes	Yes
Date	Yes	
Sector		Yes
<i>Fit Statistics</i>		
Observations	24,367	24,063
R^2	0.94526	0.95811
Within R^2	0.02213	0.83875

Table refers to Equation (2.4) and tests whether SLBs exhibit a premium. Each SLB's and its conventional bond's "twin" yield are regressed on a set of dummy variables including issuer, rating, currency, sector, and time fixed effects. Controls for liquidity (bid-ask spread) and maturity are added and a "green" dummy specifies the yield differential between the bond pairs. The second specification adds macrovariables, i.e., the VIX, the short-term 3-month US-treasury rate, and the long 10-year US-treasury rate. Heteroscedasticity-robust standard errors are in parentheses. *** implies significance at the 1% level, ** at the 5% level and * at the 10% level.

A.3 The Nelson–Siegel–Svensson Method

A parametric model, the Nelson–Siegel–Svensson (NSS model), is applied to infer theoretical prices (and yields) over the maturity spectrum visualized by a yield curve for each of the 45 SLB-bond issuers. Nelson and Siegel established a parsimonious nonlinear optimization model where parameters reflect the typical shapes of yield curve (Nelson and Siegel, 1987). By integrating the solution of a second order-differential equation, they specify the spot rate (zero-coupon bond yield) as a function of maturity and on the below defined beta parameters of the following form:

$$\begin{aligned}
 z(b, m) = & b_0 + b_1 \left(\frac{1 - \exp\left(-\frac{m}{\lambda_1}\right)}{m/\lambda_1} \right) \\
 & + b_2 \left(\frac{1 - \exp\left(-\frac{m}{\lambda_1}\right)}{m/\lambda_1} - \exp\left(-\frac{m}{\lambda_1}\right) \right) \\
 & + b_3 \left(\frac{1 - \exp\left(-\frac{m}{\lambda_2}\right)}{m/\lambda_2} - \exp\left(-\frac{m}{\lambda_2}\right) \right)
 \end{aligned} \tag{2.5}$$

The NSS-model, which is extensively used by central banks,¹³ describes the term structure of interest rates (spot rates) by six parameters that represent long-run level of interest, the slope and the curvature.

β_0 represents the long-term interest rate and is always greater zero, β_1 is the spread between the long- and the short-term interest rate and generates a monotonically increasing (if β_1 is negative) or decreasing function (if β_1 is positive), while the β_2 parameter generates a hump-shape (if positive) or U-shaped (if negative) function. λ_1 specifies the position of the hump or U-shape (decay factor). The last term β_3 with an additional λ -parameter adds an additional turning point and is an extension of the NS- model made by Svensson to better capture more complex term structures in the short and in the long-term (Svensson 1994). From the sport rate, Svensson derives the discount function as of the form:

$$d(m, \mathbf{b}) = \exp \left(- \left(\frac{z(t, m, \mathbf{b})}{100} \right) \cdot m \right) \tag{2.6}$$

¹³The ECB estimates daily yield curves for the euro area and derives forward and par yield curves based on the NSS method

This equation discounts each payment flow to its present value with varying maturity-related spot rates. Finally, the discount function is used to derive theoretical prices and yields over the maturity spectrum and those are compared with the actual observed ones that trade in the market by solving an optimization problem of the form

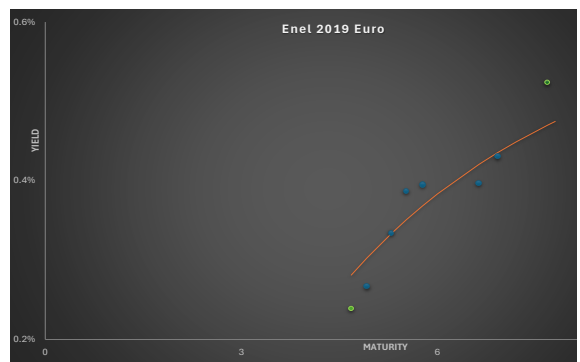
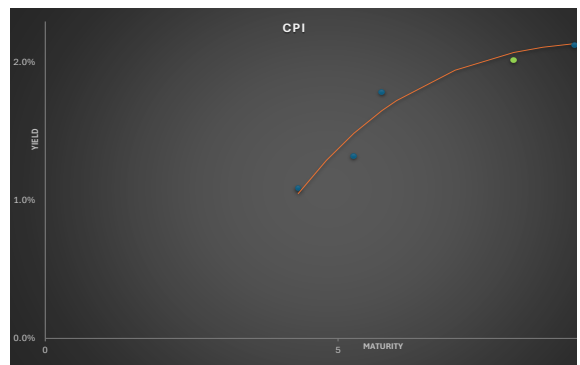
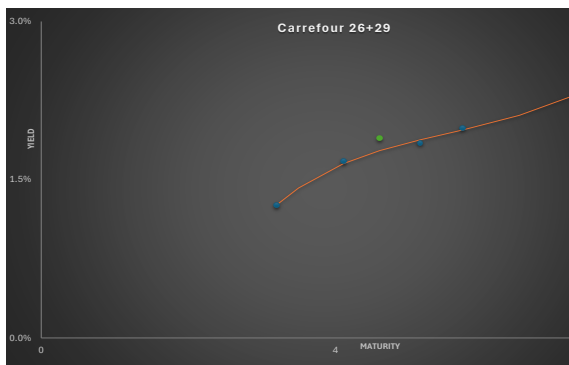
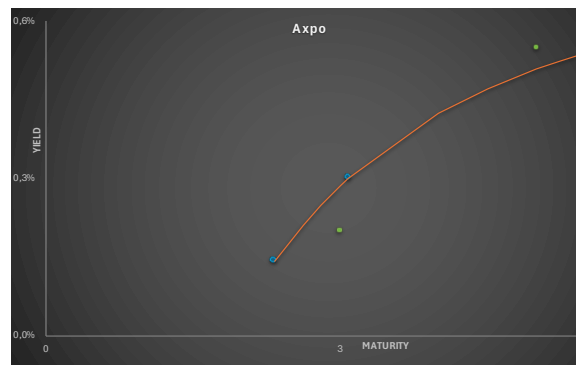
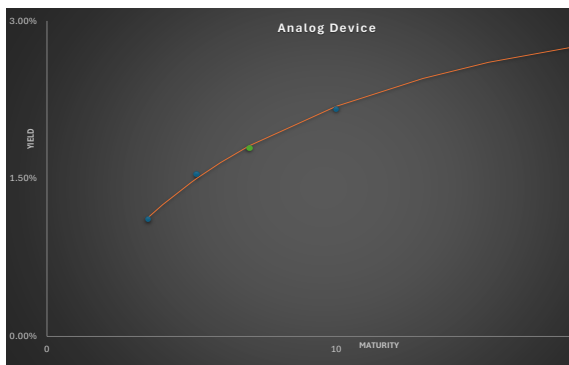
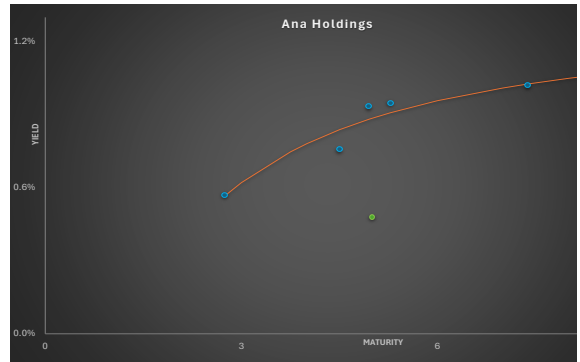
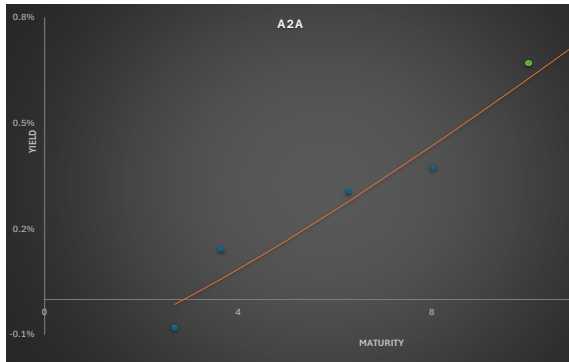
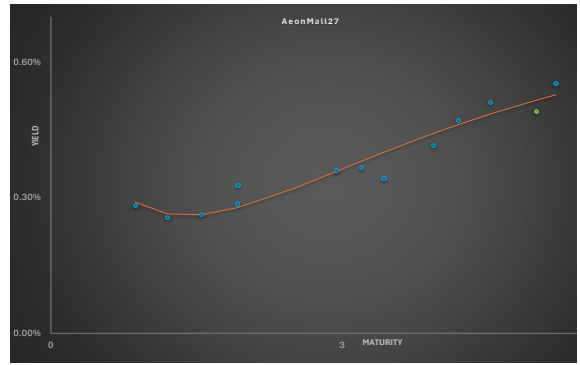
$$\sum_{i=1}^N (y_{i,t} - \tilde{y}_{i,t}(b_t))^2$$

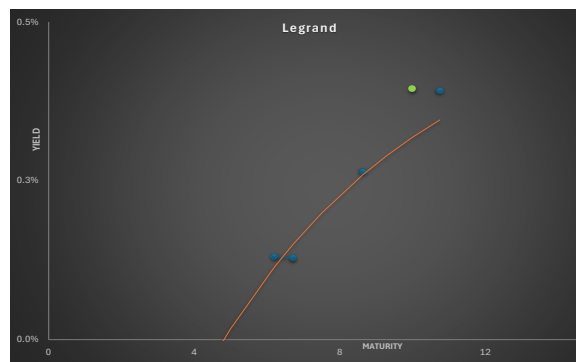
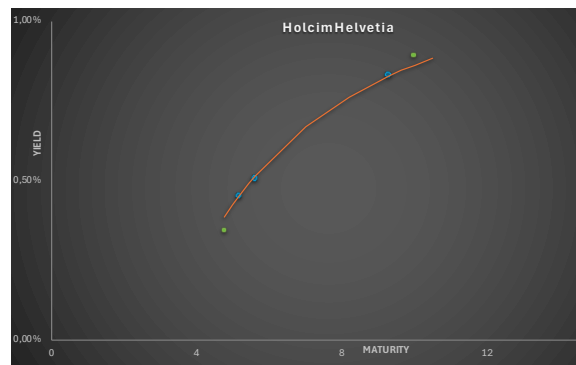
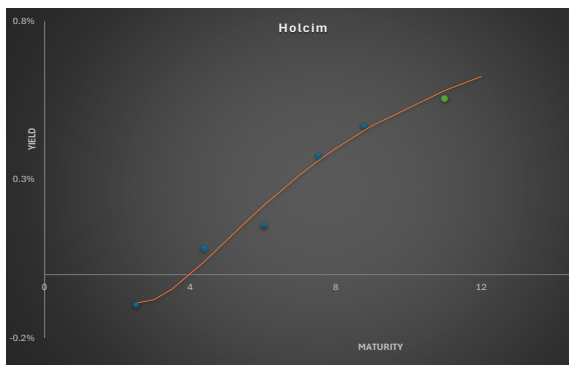
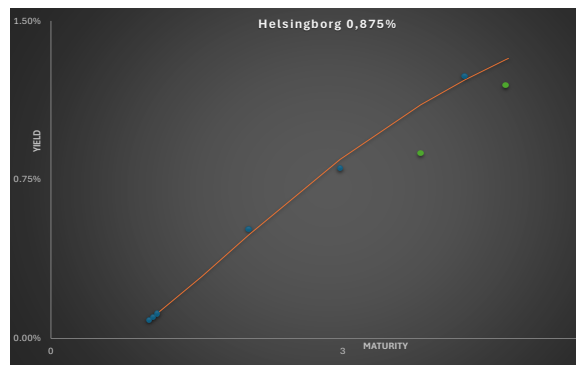
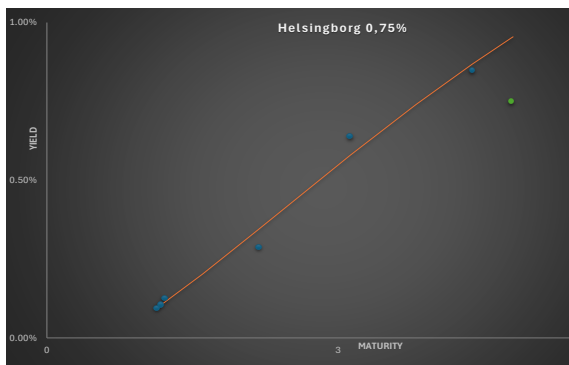
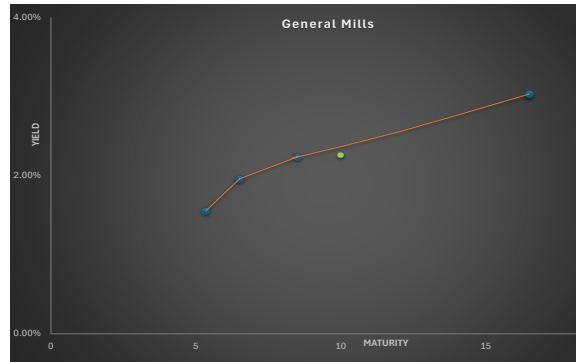
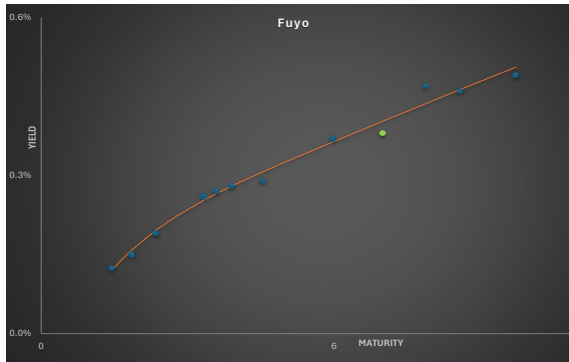
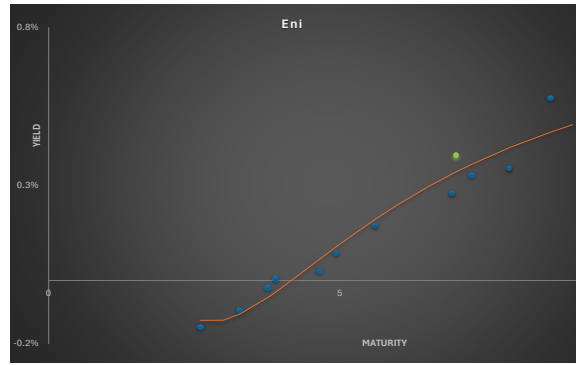
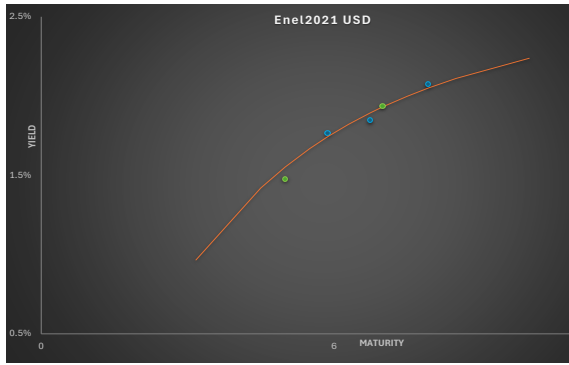
that is determined to minimize the sum of squared yield deviations. The final b estimates are used to plot the yield curves for each issuer. Since deviations between actual and NSS estimated yields have been minimized, the curve will approximately fit the observed yields.

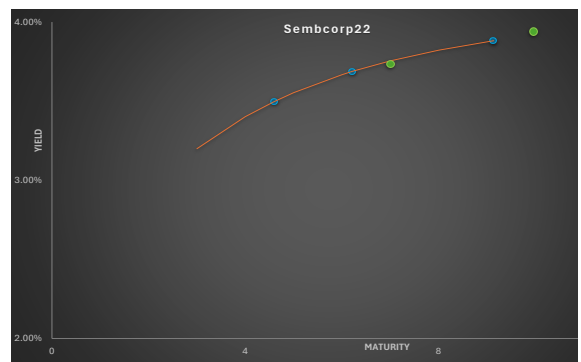
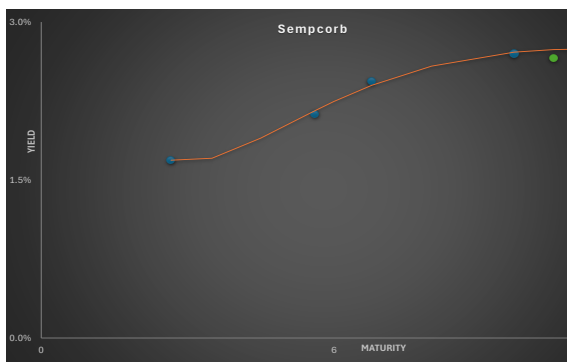
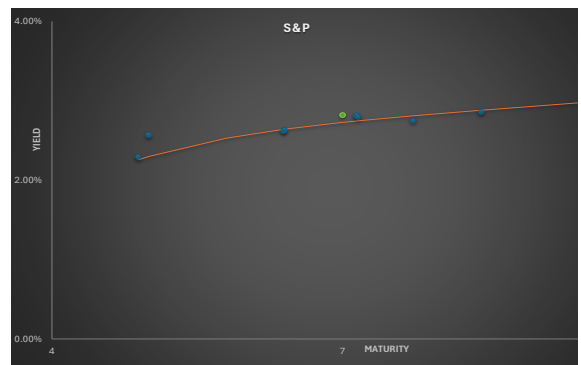
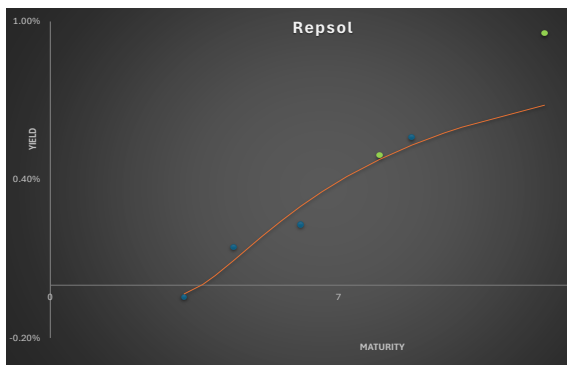
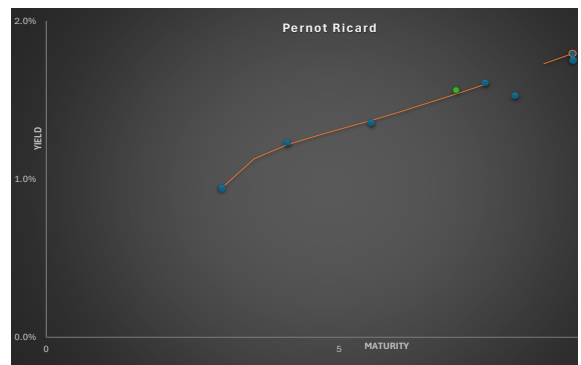
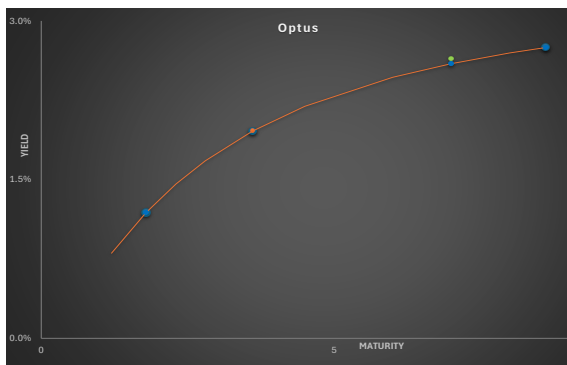
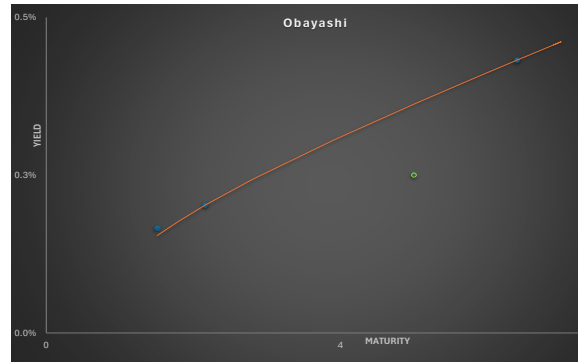
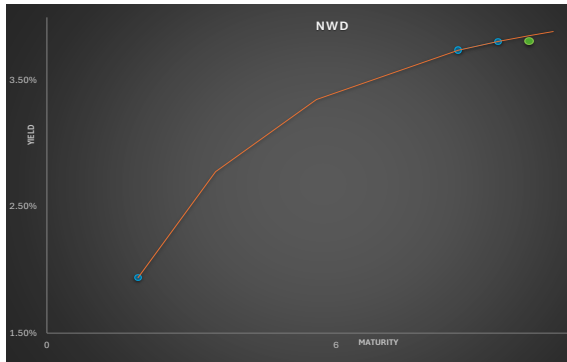
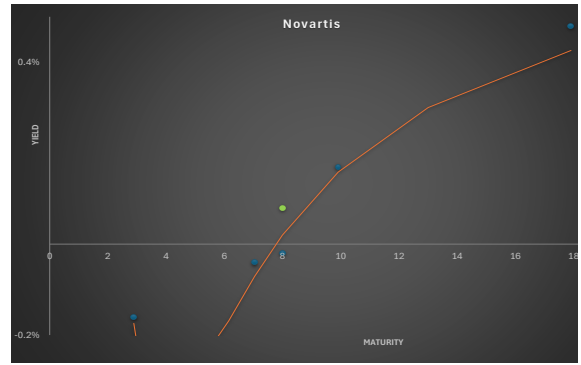
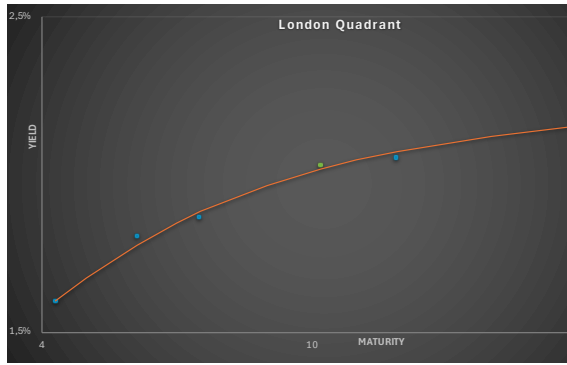
A.4 Fitted Yield Curves

To examine if SLBs exhibit a premium (implying that investors pay higher prices and therefore accept lower yield to the benefit of the issuer) at issuance, yield curves are fitted with the Nelson–Siegel–Svensson method (NSS) to infer theoretical yields over the bonds’ remaining time to maturity spectrum by fitting yield curves for the SLB-issuing firm on the issuance day.

Afterward, the yield of the SLB at issuance is compared to the NSS yield at the same residual maturity. If the SLB yield is below the curve, this is evidence of a premium, as investors accept a lower yield.







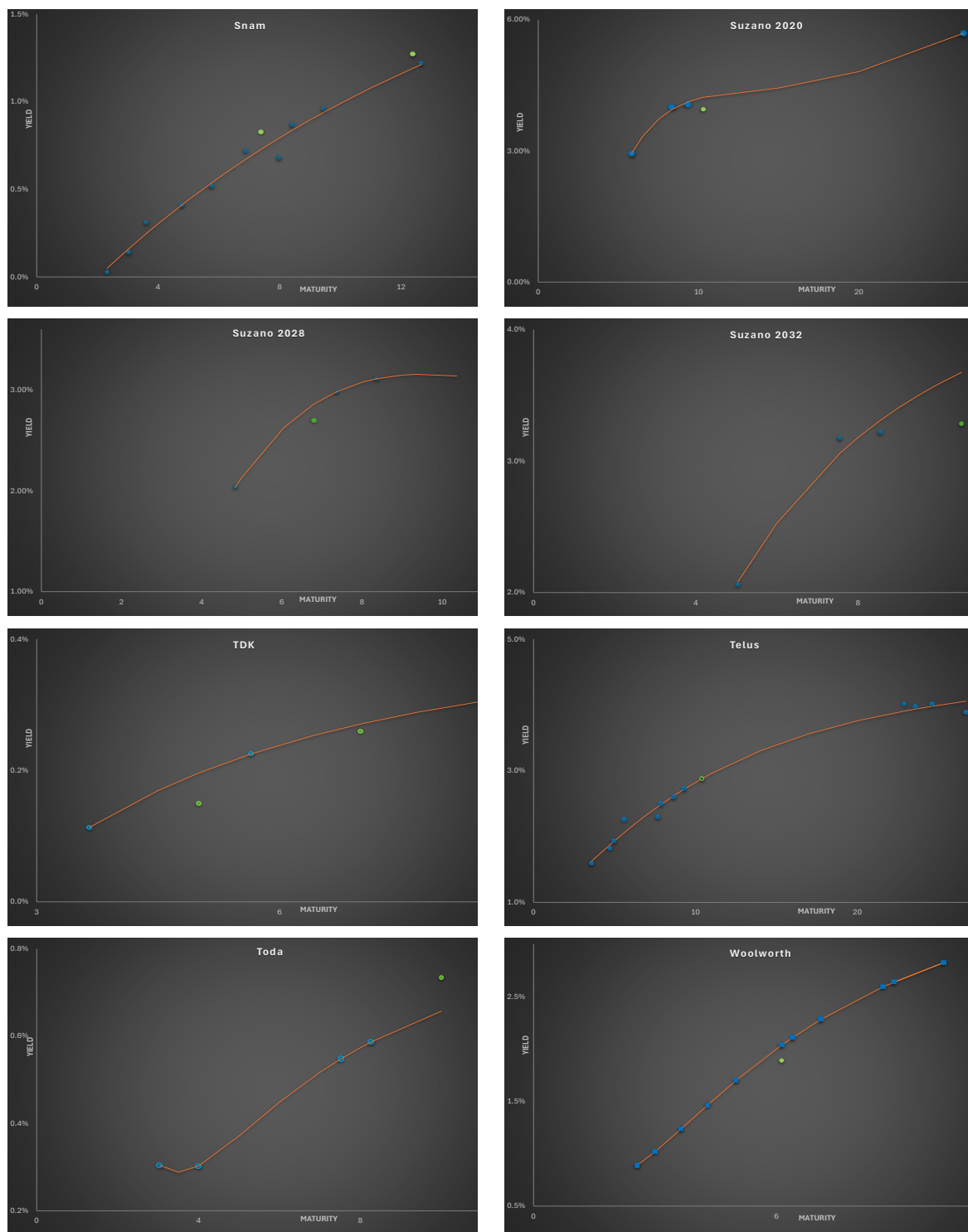


Figure A.4.1: Yield Curves estimated by Nelson–Siegel–Svensson method. Plots yield curves for 45 issuers on the SLB-issuance pricing date. The blue dots are the observed yields of the issuer’s conventional bonds that trade on the secondary market. A yield curve is fitted with the Nelson- Siegel Svensson method. Finally, the SLB (green dot) is overlaid. A SLB below its curve implies a sustainable premium, greenium.

3 Generating shareholder value through the announcement of sustainability-linked bond issuance

Abstract

Recent years witnessed a rapid growth of ESG-related debt instruments. The most recent ones are Sustainability- Linked Bonds (SLBs), whose cash flows are linked to the issuers' achievement of predefined sustainability performance targets. By applying an event study, this paper examines how the stock market responds to the announcement of issuing SLBs. Over a short event window of three trading days around the announcement, the cumulative abnormal returns are positive and significant. The highest excess returns of 0.32 % are observed on the day of the announcement. This is consistent with a signaling argument that by issuing SLBs, issuers reveal their commitment toward the performance target and are rewarded by the stock market.

Keywords: Sustainable finance, Sustainability-linked bonds, Event Study

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3.1 Introduction

In the wake of the 2015 Paris Agreement, policymakers legally committed themselves to hold “the increase in the global average temperature to well below 2°C above pre-industrial levels” (UN, 2015)¹⁴ and pursue efforts to limit the increase to 1.5°C by reaching net zero emissions by the middle of the 21st century. Consequently, many sectors face new risks summarized in the superordinate categories of physical and transitory risks that are, for instance, caused by natural disasters or changes in legislation. Capital markets are one way that could help companies hedge risks by raising large amounts of capital today. Thus, the shift towards a low-carbon economy is leading to rapid growth of green and ESG-related assets. Currently, the bond market features green and other ESG-related bonds. The newest ESG-related fixed income instrument is Sustainable-Linked Bonds which are linked to the issuer’s achievement of pre-defined sustainability targets. Beyond this, the market for green loans, green asset-backed securities, or green mortgage-backed securities has widely expanded. For instance, according to the IMF, ESG-related debt issuance topped \$1.6 tn in 2021, exceeding 2020’s record issuance by 116%.¹⁵ Simultaneously, the number of companies incorporating sustainability efforts into their business strategies is rising, (Deloitte, 2022)¹⁶ and more investors are tying their investment decisions towards firms’ ESG/CSR performance, reflected in a steadily increasing demand for sustainable funds, stock, and bond indices. As a result, firm valuation is not only dependent on financial performance anymore, but also on the corporates’ management strategies to mitigate challenges from the environmental and social shift (Velte, 2020).

There is now a vast academic literature on whether corporate sustainability-performance and sustainable investing strategies result in better financial performance. Based on 1400 surveyed studies, sustainability is positively associated with corporate financial performance, while ESG-investing strategies are on average indistinguishable from conventional investments (Atz et al., 2023). However, studies that regress portfolio returns or other annual measures of a firm’s profitability on a low frequency ESG-proxy (for instance a score) can be affected by reverse causality issues (Krueger, 2015): Are more sustainability-oriented firms more profitable (“Doing well because doing good”), or, are more profitable firms more sustainable, because they can afford to direct cash flows into environmentally friendly projects (“Doing good by doing well”)?

¹⁴United Nations Framework Convention on Climate Change. Paris Agreement, 2015. https://unfccc.int/files/essential_background/convention/application/pdf/english_paris_agreement.pdf

¹⁵International Monetary Fund. ESG Monitor Q4 2021. <https://www.imfconnect.org/content/dam/imf/News%20and%20Generic%20Content/GMM/Special%20Features/ESG%20Monitor%20Q4%202021.pdf>

¹⁶Deloitte. 2022 CxO Sustainability Report. <https://www2.deloitte.com/global/en/insights/topics/strategy/2022-cxo-sustainability-report.html>

In contrast to this well-established long-run relationship, there is little empirical evidence on the question how ESG-related news translates into firm value in the short run. Among the first studies in this field are Klassen and McLaughlin (1996) who show that the stock market responds positively to environmental performance news in the short run. More recent studies have examined how the issuance of green bonds—fixed-income instruments that fund specific environmentally beneficial projects tied, for instance, to renewable energies or pollution prevention—affect a company’s share value (Flammer, 2021; Tang and Zhang, 2020).

Sustainability-Linked Bonds (SLBs), by contrast, offer more flexibility than green bonds, as they are not tied to specific projects. Instead, SLBs link their cash flows to the achievement of predefined sustainability performance targets, such as carbon reduction or corporate diversity goals. If the targets are not met, a penalty mechanism materializes, most commonly a coupon step-up. The more flexible approach of SLBs should enable more issuers to access the sustainable financing market, as the green bonds’ use-of-proceeds taxonomies do not include some “hard-to-abate” sectors like energy or manufacturing that might have fewer green expenditures (Maino, 2022). Finally, the general-purpose approach of SLBs make them attractive to firms seeking to implement company-wide sustainability efforts, rather than funding isolated projects.

Given this flexibility and potential of SLBs to incentivize sustainability efforts, this paper asks how the stock market will react to the announcement of SLB-issuance and which factors might explain the variation of the market response.

The stock market reaction to SLB issuance may differ from that of green bonds. While the majority of recent contributions find positive market reactions in the wake of green bond issuances (e.g., Tang and Zhang, 2020; Baulkaran, 2019), suggesting that investors reward firms for investing into specific and clear environmental projects aligned with a transparent ESG commitment, SLBs provide the market with more precise information updates on the company’s medium and long term ESG-strategy (eg., by when does the company seeks to have reduced its carbon emissions compared to which baseline?). Such a forward looking framework can add to shareholder value.

Another key feature of SLBs is that firms typically set their own performance indicators for sustainability targets, based on the recommendations of the International Capital Markets Association (ICMA). In addition, the ICMA provides voluntary guidelines to ensure the integrity of the SLB market, including independent verification of sustainability

targets and annual progress reports. These guidelines help building investor confidence.¹⁷

However, the use of SLBs is not without its challenges. First, there is a risk of greenwashing, where firms may set unambitious or easily achievable targets to demonstrate sustainability commitment without driving substantive change. Moreover, recent industry reports stress that SLBs are embedded with penalty structures that are too weak (Liberatore, 2021; Haq and Doumbia, 2022) lowering the issuer’s commitment to exert real effort. Additionally, regulatory oversight in the SLB market is still developing, which could lead to inconsistencies in target setting and compliance. Without strong third-party verification or regulatory standards, market participants might remain skeptical of the credibility of these instruments resulting in a more moderate stock market reaction.

To the best of my knowledge, and despite the growing popularity of SLBs, there is no academic research yet that examines how the stock market reacts to the issue of SLBs in the short term over a 3-day window around the announcement day and which SLB-characteristics might trigger a significant stock price reaction. Given SLBs’ flexible structure and their potential to incentivize company-wide sustainability, understanding how market participants respond to these instruments is critical for sustainable finance.

Currently, there are only a few studies examining the SLB-market. For instance, Kölbel and Lambillion (2022) find that SLBs trade at higher prices (lower yields) on the issuance day. The study closest to mine is the one by Berrada et al. (2022) who derive a measure that identifies the extent of mispricing of SLBs and show that overpriced SLBs result in positive stock price reactions, which consistent with a wealth transfer from bond- to shareholders. However, these studies have not explored the short-term stock market reactions to SLBs, which this study aims to do.

This empirical study is motivated by two competing views. First, on the one side markets may react positively to the announcement of an SLB issuing firm, because of the new information provided regarding the firm’s strategy of combating climate change and of mitigating the physical and transition risks. Moreover, since investors are endowed with an instrument that makes the issuer liable, one would expect a stronger stock market reaction due to a more credible announcement. Consistent with the signaling effect in the green bond market (Flammer, 2021) SLBs with more ambitious performance targets could trigger stronger stock market reactions. In addition, if the targets are not met, the signaling effect of higher coupon payments could be considered credible by the market

¹⁷The ICMA is a not-for-profit association that provides industry-driven standards, like the Sustainability-Linked Bond Principles. Those principles have five (voluntary) core components: Selection of a Key Performance Indicator, calibration of a Sustainability-Performance target, specification of the bond characteristics, reporting, and verification. All bonds in my sample implemented these voluntary process guidelines, which are common industry standards.

and share prices react positively shortly after the issue. Finally, as bond investors may pay higher prices (and consequently sacrifice return) to hold ESG-related bonds, which is often defined as a “greenium” (e.g. Zerbib, 2019; Karpf and Mandel, 2017; Bachelet et al., 2019) potential lower cost of capital for the benefit of the issuer could result in a wealth-transfer from bondholders to shareholders (Berrada et al., 2022).

On the other side, markets could react negatively. A new (sustainable) strategy causes uncertainty as to whether the new business model would remain as profitable as the previous one (Lebelle et al., 2021). Further, market participants may find the sustainability targets not ambitious enough and react negatively. In addition, a potential coupon step-up implies uncertainty to the companies’ future cash-flow and increases the issuer’s credit risk. The features of SLBs - the sustainability performance target and the penalty mechanism offer potential greenwashing channels (Kölbel and Lambillon, 2022), as targets could be set too low or the penalty mechanism could be not fierce enough which would not send a credible signal to the market.

The empirical results of this paper suggest that the stock market reacts positively to the issuance of SLBs and creates firm value in the short-term: The announcement day, on which the transaction details are communicated to the market, exhibits an average abnormal return (AAR) of 0.32%. The cumulative abnormal returns over the (-1, 1) and the (-2, 5) event windows are positive and statistically significant, ranging between 0.60% to 0.72%. Consequently, the issuance of SLBs generate shareholder value in the aftermath. Primary drivers of the positive abnormal returns seem to be the credible signal of the issuer’s commitment towards the environment, which causes short-term price pressure around the announcement day. In contrast, potentially lower cost of debt via SLB issuance, the magnitude of the penalty (that materializes if the sustainability target is not achieved), and past environmental performance of the issuer do not significantly explain the variation of abnormal returns.

The remainder of the paper is structured as follows: Section 2 reviews the related literature. Section 3 highlights the data gathering process and the applied methodology. The results of the Event Study are discussed in Section 4. Determinants of the cross-sectional variation are stressed in section 5. Section 6 provides robustness tests. Finally, section 7 concludes.

3.2 Literature Review

This study contributes to several fields of academic literature. First, it relates to the literature on how the stock markets respond to security offerings. Earlier contributions provide evidence of a significantly negative stock market reaction following the issuance of seasoned equity (Asquith and Mullins, 1986; Masulis and Kowar, 1986; Dann and Mikkelsen, 1986) and convertible debt (Mikkelsen and Partch, 1986; Dann and Mikkelsen, 1986; Eckbo, 1986), while price reactions to conventional debt offerings are typically considered “no-news” events (Eckbo, 1986; Mikkelsen and Partch, 1986). None of these studies identify factors explaining the cross-sectional variation in abnormal returns, i.e., the size of the offering, the rating of bonds or abnormal earnings in the period following the offering (Eckbo, 1986). A survey by Eckbo et al. (2007) concludes that the equity market shows no significant reaction to the issuance of conventional bonds mostly consistent with the irrelevance theories proposed by Modigliani and Miller (1958) and Miller (1977), stating that the capital structure of the firm is irrelevant for the value of a firm.

In contrast to these earlier findings with respect to traditional debt instruments, green bonds generate positive abnormal returns in the aftermath of their issuance, (Flammer, 2021; Baulkaran, 2019; Tang and Zhang, 2020; Zhou and Cui, 2019) while Lebellet et al. (2020) find negative abnormal returns. Flammer (2021) concludes that green bonds provide information about the usual details of the issue as well as a signal about the companies’ commitment to the environment. Consistent with Klassen and McLaughlin (1996) she concludes that equity markets rewards firms that announce environmental-friendly actions. Baulkaran (2019) explains the positive announcement returns through several bond- and firm-specific characteristics and shows that firm risk, measured by beta and the standard deviation of daily returns declines after issuance. Roboredo and Ugolini (2018) find spillover effects between the global green bond market and the stock market, although the connectedness is much weaker than the global fixed-income and the USD-currency market. Tang and Zhang (2020) discuss the channels of the abnormal green bond announcement returns. Although they find that a “greenium”¹⁸ (implying lower yields of green bonds compared to conventional bonds to the benefit of the issuer) does not trigger a positive stock market reaction, increased institutional ownership and improved stock liquidity after the green bond issuance would underly positive abnormal returns.

¹⁸Most of the green bond (green finance literature) investigates the pricing of green bonds both on the primary and on the secondary market. Leading contributions in the field mainly provided mixed evidence whether green bonds trade at a “greenium” implying lower yields of green bonds compared to their conventional bond twin (Zerbib, 2019; Baker et al., 2018; Hachenberg and Schiereck, 2018; Gianfrate and Peri, 2019) or, in contrast, either at higher yields as reported in Karpf and Mandel (2017) and Bachelet et al. (2019) or at no difference as in Larcker and Watts, 2021 or Flammer, 2021.

Since SLBs frame the company’s intentions as to which future CSR/ESG improvements they commit explicitly to, this work is also indirectly related to the contentious debate discussing the nexus between corporate social responsibility (CSR) and ESG effort on firm performance and firm value. Krueger (2015) investigates the equity value implications of positive and negative CSR news in the short-term and finds that investors react strongly negative to negative event news and slightly negative to positive news. More recently, the impact of ESG-news, characterized by textual analysis, on short term stock returns have been analyzed (e.g., Capelle-Blancard and Petit, 2019). While negative news are associated with a drop in market value, there is no reaction to positive news. Recent meta-analysis studies claim that CSR results in better financial performance (Atz et al., 2023; Velte, 2020; Vishwanathan et al., 2020) by enhancing firm reputation, increasing shareholder reciprocation, mitigating firm risk and strengthening innovation capacity (Vishwanathan et al., 2020). Evidence from this meta analysis supports the view of the instrumental stakeholder theory (“doing well by doing good”): by prioritizing stakeholders’ interest, companies ultimately enhance their financial performance and generate shareholder value (Berman et al., 1999). Given the soaring growth of SLBs, further research on how the stock market reacts to SLB- announcements and what might explain the variation in abnormal returns in the cross-section is warranted.

3.3 Data and Methodology

This section compiles the database of SLBs and describes the data cleaning process.

3.3.1 Data extraction, final sample and the evolution of the SLB-market

First, all bonds that are labeled as “sustainability-linked” are extracted from Refinitiv’s ESG Bond Database covering bond-specific data including the issue price, the coupon, the maturity and the amount issued. From September 2019—the month the first SLB has been issued by the Italian electric utility company Enel—until December 31, 2023, Refinitiv lists 700 SLB-issuances. Secondly, Refinitiv’s bond viewer app displays important SLBs terms, for instance the performance target, the magnitude of the step-up, the announcement day or the issuance day. Since some SLB details are partly not yet comprehensive, terms were also collected manually, based on company press releases, investor relations, the offering memorandum or bond prospectuses.

Figure 3.1 below shows the development of the market. While the issuance volume soared in 2021, it decelerated in 2022 caused by the raising interest rate environment, a blurred economic outlook, and the Ukraine war. The lowering issuance volume trend in 2022 is

both observable for other ESG-related fixed income classes (including green, social and sustainable bonds) and conventional bonds.

Figure 3.1: SLB-Issuance Volume

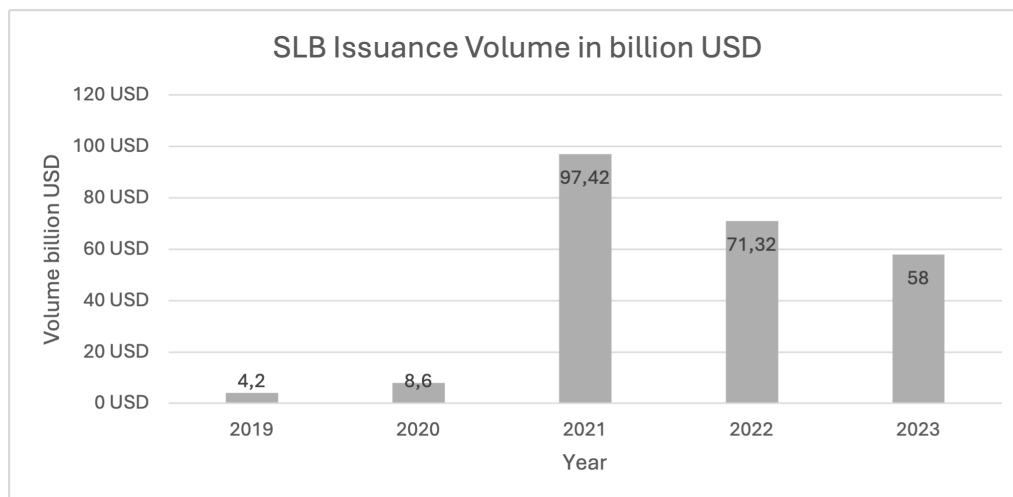


Figure 3.1: SLB Issuance Volume in Billion USD. This figure plots the amount of issued SLBs in USD between 2019 and 2023 according to data from Refinitiv’s ESG bond database.

Next, the dataset is adjusted to exclude all SLB issuers that are privately held companies. In addition, all SLBs that exhibit a bifurcated structure are dropped to avoid double-counting.¹⁹ SLBs listed on a Chinese stock exchange have been excluded, because they tend to exhibit different financial characteristics in terms of the step-up procedure and the materiality of the step-up.²⁰ In addition, only SLBs are considered that have an issued volume over 100 million dollars to have a sizeable effect on market attention. Finally, SLBs that bear a floating-coupon structure are excluded. Overall, the final sample consists of 167 SLBs. Since a company may issue several bonds-tranches with different maturities on the same day the 166 issued SLBs correspond to 135 announcement days in the final sample.

3.3.2 Event Study Methodology

To examine the stock market reaction in the aftermath of SLB issuance, I utilize the standard event study approach (Fama et al., 1969; Brown and Warner, 1985) applied in numerous studies, also in the green bond literature (e.g., Flammer, 2021; Tang and

¹⁹Some public offerings are issued both under 144a offerings and RegulationS offerings. Refinitiv lists both those offering types. To avoid double counting one type is dropped.

²⁰Usually and contrary to “Western” SLBs, SLBs from Chinese companies have a 10-bps coupon step-up penalty mechanism that materializes when the bond matures.

Zhang, 2020).

First, for each SLB issuance, the announcement day is used as the relevant pricing date, i.e., the date on which terms of issuance (coupon, issue price and yield) are agreed upon the issuer and the underwriter. The announcement conveys the new relevant bond pricing information and additionally updates the market on the extent to which sustainability targets and the consequences of not achieving them are anchored in the final terms.²¹

To study shareholder wealth effects, I calculate daily expected returns using the market model and the Fama-French three factor model. The models are defined as:

$$R_{i,t} = \alpha_i + \beta_i \times R_{mt} + \epsilon_{it}, \quad (3.1)$$

$$R_{i,t} = \alpha_i + \beta_{i,1} \times R_{mt} + \beta_{i,2} \times \text{SMB} + \beta_{i,3} \times \text{HML} + \epsilon_{it}, \quad (3.2)$$

where $R_{i,t}$ denotes the daily closing stock return of the respective SLB-issuing firm, and R_{mt} represents the daily market return. $\beta_{i,2}$ and $\beta_{i,3}$ capture the sensitivity to the size factor (SMB) and the value factor (HML). I use the leading market index of the country where the SLB-issuing company is headquartered. Country indices have proven to deliver better goodness of fit statistics and lower residual standard errors than a global stock market index like the MSCI World as Appendix B1 reports. For the market model (abnormal) returns not explained by the relation between the security's return and the return of the stock market are captured by the disturbance term ϵ_{it} . The coefficients α_i and β_i of the market model are estimated by OLS following the "standard" procedure of using 250 trading days ending 30 days before the considered event date (McWilliams and Siegel, 1997; Mac Kinlay, 1997).²² Next, the estimated parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$ are used to predict the expected return of security i over the event window τ and the security i 's abnormal return is defined as:

$$AR_{i,\tau} = R_{i,\tau} - (\hat{\alpha}_i + \hat{\beta}_i \times R_{m\tau}) \quad (3.3)$$

with $R_{i,\tau}$ being the actual observed stock return of issuer i during the event window. Formally, abnormal returns can be interpreted as the prediction error of the applied

²¹In contrast, the issuance day is the settlement day, where the bond is delivered to the investor. So, the announcement day conveys the relevant new information.

²²By using a buffer of 30 days it is ensured that the parameter estimates are not affected by event-related information.

model calculated on an out of sample basis i.e., the length of the event window τ .

Since too long event windows reduce the power of the test statistic (Brown and Warner, 1980; Brown and Warner, 1985) and are influenced by confounding events making it difficult to assess if the stock market reaction is due to the event of interest, a short estimation window is chosen, ranging between (-1,1) and (-2,5) days around the announcement day.

For each issuer the daily abnormal return around the event window is summed. Finally, the cumulative average abnormal return $\overline{\text{CAR}}$ of all issuers of the sample is computed.

$$\overline{\text{CAR}}_\tau = \frac{1}{N} \sum_{i=1}^n \text{CAR}_{i,\tau} \quad (3.4)$$

The diagnostics tests of appendix B1 (in particular see Table B.1.3. Statistical Test Results) show that the cumulative abnormal returns are asymptotically normally distributed in the cross-section and a standard t-test is utilized under the null hypothesis that the issuance of SLBs does not affect stock returns. The t-test is adjusted for the length of the event window to ensure that the standard error calculation—based on the individual residual standard errors of the estimation window—better reflects the variability of abnormal returns over the event window. Appendix B.2 discusses the applied tests in greater detail.

By applying events studies, the reliability of results and the statistical inference depend on the assumptions that markets are efficient, the event was unanticipated, and there were no confounding events during the event window (Siegel and MacWilliams, 1997). Therefore, I control for confounding events by eliminating the firms from the sample that have confounding events over shortest event window, i.e. the (-1,1) interval, reducing the sample size to the final sample of 135 issuance events. Confounding events include firm-specific events that distort the market reaction during the event. Possible events are, for instance, the release of earnings reports, the announcement of mergers and acquisitions, the update of financial year's earnings or other financial figures, the roll-out of new products, dividend announcements, major executive changes, a change in a firms' credit rating or cyber-attacks.

Finally, it remains difficult to dissect to what extent the market has anticipated the announcement of SLBs. Some issuers have already published sustainable finance frameworks

in advance of the SLB-announcement.²³

Consequently, the market could have already priced in some information prior to the SLB-announcement day. However, the announcement day provides detailed information which exact ESG-target is tied to the SLB-issuance, by which indicator the performance is measured, when the coupon would first step-up (provided that the target is not achieved), and how the terms of issuances are agreed upon between the issuer and the underwriter. Therefore, the broader market should receive some new information on the announcement day.²⁴

3.4 Event Study Results

The cumulative average abnormal returns are reported below in Table 3.1. The average cumulative abnormal returns are both positive and significant over the (-1,1) and the (-2,5) event window ranging between 0.60% and 0.72% for the market model and 0.58% and 0.87% for the Fama-French 3 factor model. By extending the interval boundaries, the abnormal returns remain positive, albeit non-significant.

Table 3.1: CAARs over different event windows estimated by the market model and the 3-Factor Fama-French model

Panel A. Market Model			
Window	CAAR	T-stat	Pos:Neg
[-1,1]	0.60	2.26***	83:52
[-2,5]	0.72	1.67*	75:60
[-5,10]	0.94	1.53	74:61
[-5,20]	0.43	0.55	71:64
Panel B. 3 Factor Model			
Window	CAAR	T-stat	Pos:Neg
[-1,1]	0.58	2.00**	77:58
[-2,5]	0.87	1.83*	80:55
[-5,10]	1.08	1.60	72:63
[-5,20]	0.36	0.42	70:65

²³ A Sustainable Financing Framework provides general information to the stakeholders how the sustainable strategy is implemented. It is emphasized how ESG considerations are integrated into the overall strategy of the company. Some frameworks also stress how their strategy is aligned with the treaty of the Paris Agreement.

²⁴ A detailed discussion can be found in the robustness chapter.

*This table reports the cumulative average abnormal returns calculated using the market model and the Fama-French 3-Factor Model. The market index is represented by country-specific indexes in which the company is domiciled. The sample consists of $N=135$ SLB issuance events. I use a 250-day estimation period lasting from 280 to 30 days prior to the announcement date. The $(-1,1)$ event window controls for confounding events which are for instance: earnings reports, dividend announcements, roll out of new major products, the acquisition of another company, or the update of key financial figures. Panel A uses a standard market model to calculate CARs, while Panel B uses the global Fama and French 3-Factor Model. *Indicate statistical significance at the 10% level, ** indicate statistical significance at the 5% level, *** indicate statistical significance at the 1% level.*

The CAARs and the daily average abnormal returns over the $(-2,5)$ event window are plotted below in figure 3.2.

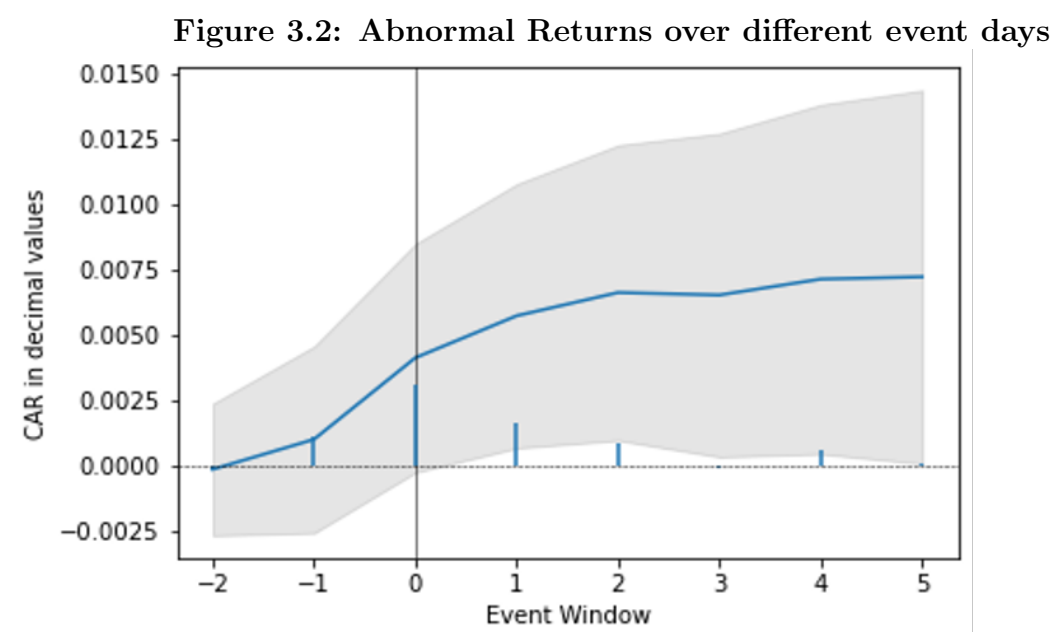


Figure 3.2: Figure 3.2 blue's curve plots the cumulative average abnormal return of 135 announcement days over the $(-2,5)$ event window. The blue bars on the horizontal line represent the average abnormal return on the respective day of the event window.

The highest abnormal returns are measured on the announcement day ($\tau = 0$) generating abnormal returns of around 0.32%. In the aftermath of the SLB issuance a clear and significant upward trend is evident that weakens two days after the announcement day. Consequently, the issuance of SLBs increases stock prices on average. The positive stock market reaction is consistent with former results by Klassen and McLaughlin (1996) who showed that environmental management and positive events results in positive abnormal returns and with recent green bond literature providing first evidence that the green label signals a firms' commitment towards the environment resulting in higher firm value (Flammer, 2021; Tang and Zhang, 2020). The positive market response indicates that

the signaling effect is particularly strong for SLBs given their unique structural features.

However, the positive, albeit decreasing, non-significant abnormal returns over the $(-5, 10)$ and $(-5, 20)$ event windows indicate that the positive reaction reverses after the issuance, consistent with the price pressure hypothesis that posits that the initial response is based on temporary buying pressure rather than a re-evaluation of firm value (e.g., Barber and Loeffler, 1993).²⁵ While price pressure offers an alternative explanation for the observed short-term returns, it does not undermine the signaling argument. The SLB structure inherently communicates the issuer’s commitment to sustainability, providing credible information that can positively influence investor perceptions.

3.5 Cross-Sectional Variation of Abnormal Returns

In this section, the drivers of abnormal returns are examined in a cross-sectional analysis. First, the SLB-issuing companies are split into subsamples with respect to bond-specific targets including the penalty mechanism, the type of the penalty, the magnitude of the penalty related to the “original” coupon and the ESG-performance of the company. To examine the relation between abnormal returns and SLB-characteristics in more depth, the cumulative abnormal returns are regressed on a set of controls proxying bond-specific, issuer-specific, and SLB-related variables.

3.5.1 Subsample Split

Table 3.2 below presents estimation results on the cumulative average abnormal returns for samples split according to different SLB characteristics. First, Panel A and B examine how the SLB penalty mechanism affects stock returns. SLBs with a step-up penalty yield slightly significant abnormal returns of 0.52%, whereas SLBs with other penalty mechanisms (redemption premium, donations or purchasing carbon offsets) exhibit higher but statistically insignificant abnormal returns. Consequently, investors may view step-up penalties as a more credible commitment from the issuer compared to other penalties as donations or carbon offsets, which might be seen as a more symbolic act less likely to impose financial discipline.

In Panel B, the sample is split according to the magnitude of the penalty relative to the coupon, with the penalty variable divided at the median. Strikingly, a higher total

²⁵There is an extensive literature investigating how stocks respond to second hand information provided to the mass investing public community. Many studies find analysts’ recommendation result in short positive price pressure that reverse afterwards (Davis and Canes, 1978; Liu et al., 1990; Barber and Loeffler, 1993).

penalty above the median is associated with higher abnormal returns. This outcome implies that markets might not perceive higher penalties as a risk, potentially due to market expectations that issuers set sustainability targets with a high likelihood of being met, thereby reducing the risk of penalty activation. Panels C through E investigate whether credible external sustainability frameworks help assure investors of the issuer's commitment to sustainability. Panel C distinguishes between companies that have aligned their targets with the Science Based Targets-initiative (SBTi), a collaboration between leading environmental organizations which develop standards and tools how companies can reach net-zero emissions by 2050, in line with limiting global warming to 1.5°C.²⁶ SBTi-committed firms exhibit significant and higher abnormal returns of 0.73% than non SBTi-committed firms (0.44%). This alignment with SBTi standards likely increases investor confidence by emphasizing accountability and signaling a firm's alignment with the Paris Agreement goals.²⁷

Contrary, Panel D states that firms with an ESG combined score above the median exhibit lower abnormal returns (0.44%) than firms with a lower ESG combined score (0.75%). The backward-looking nature of ESG scores may not fully capture forward-looking commitments associated with SLBs. The signaling effect of SLBs is more founded on future sustainability targets, which are not captured by static ESG-score measures. Panel E indicates that first issuers have higher abnormal returns than seasoned issuers suggesting that first-time issuance are seen as a stronger signal for the company's shift toward sustainable finance. This finding aligns with previous research on green bonds (Flammer, 2021): after the first issuance of an SLB, market participants have become accustomed to the firms sustainable commitment, consequently the market reaction is lower. Finally, Panel F splits according to the type of the target. The carbon target has a positive and slightly significant impact on the cumulative average abnormal returns, while non-carbon targets exhibit also significant returns. Carbon targets may offer investors a more measurable and tangible framework, often aligning more closely with science-based goals and standards like SBTi. Carbon metrics also benefit from longer reporting histories.

²⁶Science-based Target Initiative. <https://sciencebasedtargets.org>

²⁷The Paris Agreement was adopted in 2015 and is a legally binding treaty that combats climate change by limiting global warming to well below 2 degrees Celsius above pre-industrial levels.

Table 3.2: Sample splits according to different SLB-characteristics

Panel A	Step-Up	Other Penalty
CAR	0.52 (1.70)*	0.87 (1.62)
Observations	105	30
Panel B	High Penalty	Low Penalty
CAR	0.81 (2.27)**	0.42 (1.04)
Observations	66	67
Panel C	SBTi	No SBTi
CAR	0.73 (2.32)**	0.44 (0.98)
Observations	74	61
Panel D	High ESG-Score	Low ESG-Score
CAR	0.44 (1.16)	0.75 (1.90)*
Observations	63	64
Panel E	Fist Issuance	Seasoned Issuance
CAR	0.73 (2.13)**	0.32 (0.81)
Observations	91	44
Panel F	Carbon Target	No Carbon Target
CAR	0.49 (1.66)*	1.12 (1.72)*
Observations	109	23

Table 3.2 reports the cumulative average abnormal returns (CARs) over the $(-1,1)$ event window for different subsamples by applying the market model. Panel A splits the sample according to the penalty mechanism of the SLB. Panel B distinguishes between a high and a low penalty by relating the cumulative magnitude of the penalty to the original coupon of the SLB ((Total amount of the penalty)/(original coupon)). Panel C divides the issuers if they have joined the Science Based Targets-initiative prior to the SLB-issuance. In Panel D the sample is divided into subsamples based on the ESG-Controversy Score in the year preceding the issuance. High Controversy scores are firms with a score above the median, low ESG-controversy scoring firms are below the median. Panel E splits the sample as to whether the company issued its first SLB or a seasoned one. Finally, panel F distinguishes according to if the target is carbon related or not. T-test statistics are reported in parentheses. *Indicate statistical significance at the 10% level, ** indicate statistical significance at the 5% level, *** indicate statistical significance at the 1% level.

3.5.2 Regression Analysis

To identify potential drivers of abnormal returns in more detail, a multivariate regression

analysis with the following specification is performed:

$$CAR_i = \alpha + \beta_1 \text{ bond-specific} + \beta_2 \text{ firm-specific} + \beta_3 \text{ SLB-specific} + u_i \quad (3.5)$$

The impact of bond-specific variables - in terms of the coupon and the maturity - and firm-specific variables - proxying the size (log of total assets), the profitability (return on assets and EBITDA-ratio), the liquidity (operating cash-flow) or the debt ratio (leverage ratio) – on cumulative abnormal returns has been investigated prior (i.e. Eckbo, 1986; Godlewski et al., 2013; Baulkaran, 2019) with mixed evidence.

Column 1 of Table 3.3 below regresses the cumulative abnormal returns -calculated by using domestic indices – on a set of bond- and firm specific controls.

The negative and (in)significant coupon coefficient suggests that the market reaction is lower for issuers with higher coupons, possibly reflecting an inverse relationship with financing costs. Although the coefficients often have the expected sign, most firm-specific variables exhibit low explanatory power. The market reaction is positively related to the size of the firm, the profitability (proxied by the EBITDA-Margin) and the cash-flow rate. To account for unobserved heterogeneity each modification adds a set of dummy fixed effects including sector, currency and country fixed effects.

Column 2 adds SLB-specific controls. Hypothetically, the financial structure of the SLBs could explain the variation of the abnormal returns as higher penalties could result in a negative market reaction. First, by using a dummy variable equal to 1 if the SLB has a coupon-step up penalty and zero otherwise (other penalties could be donations, premium payments at maturity or purchasing carbon offsets) it is evident the market reacts more negative to a coupon step-up penalty, albeit the effect is not significant.

Confirming the results of the individual sample splits, abnormal returns are not negatively affected by the magnitude of the penalty (High Penalty variable). A penalty above the median does not result in a negative market reaction, on the contrary, the market reaction is even more positive, although statistically insignificant. This supports the findings of Kölbel and Lambillion (2022) and Poggensee (2025) examining the pricing of SLBs on the primary bond market: the magnitude of the sustainability premium SLBs are benefiting from is not driven by the magnitude of the penalty. Equity investors appear unfazed by penalty size, potentially because they expect targets to be realistic and achievable.

Table 3.3: Cross-Sectional Regression

Dependent Variable: Model:	CAR (-1, 1)		
	Bond+ Issuer-Specific	SLB-Related	SLB-Premium
<i>Variables</i>			
Coupon	-0.202* (0.122)	-0.154 (0.148)	-0.330 (0.289)
Maturity	0.000 (0.001)	-0.001 (0.001)	-0.002 (0.002)
Total Assets	0.011** (0.005)	0.012** (0.005)	0.015* (0.007)
Leverage	-0.017 (0.019)	0.002 (0.020)	-0.053 (0.033)
EBITDA-Margin	0.037* (0.021)	0.034 (0.021)	0.050* (0.027)
TobinQ	-0.006* (0.003)	-0.008** (0.004)	-0.021** (0.010)
CashFlow	0.024 (0.043)	0.030 (0.043)	
Step-Up Penalty		-0.009 (0.007)	
High Penalty		0.002 (0.007)	0.005 (0.008)
SBti		0.012* (0.006)	0.011 (0.015)
First Issuance		0.004 (0.004)	-0.002 (0.010)
ESG-Combined Score		0.000 (0.000)	0.000 (0.000)
SLB-Premium			0.001 (0.026)
<i>Fixed-effects</i>			
Sector	Yes	Yes	Yes
Country	Yes	Yes	
Currency			Yes
<i>Fit statistics</i>			
Observations	125	119	53
RMSE	0.01640	0.01594	0.01313
Adjusted R ²	0.13506	0.12453	0.32393
F-test	1.4965	1.3996	1.9966

*This table displays the estimations of OLS regression using a domestic market index. The dependent variable is the cumulative abnormal return (CAR) over the (-1, 1) event window. The first column presents bond-specific controls and issuer-specific controls in the year preceding the announcement of the SLB issuance. Coupon is the interest rate the issuer pays per annum. Maturity is the number of years to maturity. Total Assets is the logarithm of total assets. Leverage is defined as total debt/total assets. The EBITDA margin is denominated in decimal values. The Cash Flow is defined as operating cash flow/total assets, whereas Tobin's Q is defined as Market Cap/Total Assets. Columns 2 and 3 add SLB-related variables. Step-Up Penalty is a dummy equal to 1 if the SLB's penalty mechanism is a coupon step-up, and zero otherwise. High Penalty is a dummy equal to 1 if the median penalty (measured by (Total amount of the penalty)/(original coupon)) is above its median value, and zero otherwise. SBTi is a dummy equal to 1 if the issuing firm has committed to science-based targets prior to the SLB issue, and zero otherwise. First Issuance is a categorical variable that takes 1 if the firm announces its first SLB issue, and zero if the issuance was a seasoned one. The ESG combined score is based on Refinitiv's ESG score and an ESG Controversy score assessing negative exposure in ESG-related areas (e.g., a lawsuit because of pollution). Column 3 adds an SLB-Premium variable, which is the yield differential between the SLB's yield at issuance and a (synthetic) conventional bond's yield at the same residual maturity inferred by fitting a yield curve. By fitting yield curves with the NSS method and comparing them to a (theoretical) yield of a conventional bond with the same residual maturity, a sustainability premium is defined. The differential is defined as yield conventional bond – yield SLB; hence, a positive value indicates a premium. Heteroskedasticity-robust standard errors in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1.*

The SLB-specific variables, including the SBTi commitment, ESG score, and First Issuance, test the signaling hypothesis: a credible commitment to sustainability should result in positive market reaction, similar to green bonds (Flammer, 2021). Although the coefficients have the expected signs, only the SBTi variable is slightly significant, suggesting that investors view the alignment to science-based targets as a credible signal of the firm's climate commitment. This supports the signaling hypothesis: quantifiable and science-backed targets are seen as credible by the market.

While the lack of significance in broad ESG-measures is contradicting the signaling hypothesis that issuers with a more credible profile may exhibit higher stock returns in the aftermath of SLB-issuance, the backward-looking ESG-scores may not capture the forward-looking commitments the SLBs provide and the market reacts to. Investors may place more weight on the specific targets outlined in the bond's structure rather than on broad and generalized ESG ratings. To test the robustness of this finding, Appendix B.3 and Table B.3.1 include regressions with alternative ESG measures - including Environmental Score, Emission-Intensity Score, and changes in emission intensity per revenue preceding the SLB issuance. None of these alternative metrics significantly explain the variation in cross-sectional abnormal returns, underscoring the distinct signaling impact of SLB-specific features over general ESG measures.

In sum, the results suggest that SLB-specific characteristics, particularly SBTi commitments, are more robust signals of sustainability than broader ESG profiles, likely due to the clear, forward-looking nature of SLBs. Unlike green bonds, SLBs currently lack third-party certification, although the Climate Bond Initiative (CBI) has recently launched a methodology for assessing SLB quality.²⁸

This aligns with the conclusions in Section 3.4, where both credible SLB signals and short-term price pressure were identified as primary drivers of positive abnormal returns. While price pressure may contribute to initial market reactions, the structure and rigorous targets within SLBs reinforce their unique signaling power.

3.5.3 Financing Cost Channel

Lower cost of debt, which are reflected in subsidized financing from investors to hold sustainable assets could be a potential source of positive abnormal returns around the announcement of SLB-issuance. As recent studies conclude, SLBs could trade at a premium, implying that investors pay higher prices and consequently sacrifice return to hold sustainability-linked assets both on the primary and on the secondary market (Kölbel and Lambillon, 2022; Poggensee, 2025). Therefore, the issuance of SLBs that trade at a premium (i.e. higher prices and lower yields) could be good news to shareholders as the issuing firm refinances itself at lower cost of capital suggesting a wealth transfer from bond- to shareholders (Berrada et al., 2022). To examine if SLBs trading at a premium at issuance I apply the Nelson-Siegel-Svensson (NSS) method (Nelson and Siegel, 1987; Svensson, 1994) to infer (theoretical) yields over the bonds' remaining time to maturity spectrum by fitting yield curves for the SLB-issuing firm on the announcement day. Afterwards, the yield of the SLB is overlayed to determine whether its yield at issuance is below, in line or above its curve. If an SLB bond is below its yield curve investors receive a lower yield and issuers face lower cost of debt as they would have expected to receive if they would had held (issued) a conventional bond which is interpreted as evidence for sustainability premium investors pay.

Column 3 of Table 3.3 reports the results of the abnormal returns regressed on the differential (yield conventional bond – yield SLB, hence a positive value is evidence for a sustainability premium) between the SLB and its yield curve and the prior bond- and firm characteristics. Since the SLB premium is not significantly associated with higher cumulative abnormal returns there is no evidence that the financing cost channel is the driving force of positive announcement returns, consistent with the finding for green bonds (Tang and Zhang, 2020).

²⁸CBI. 2023, Sustainability Report. https://www.climatebonds.net/files/files/CBI_Method_SLBD.pdf

3.6 Robustness

The robustness of the results is checked in the following ways. First, instead of using domestic indexes as a proxy for market returns, I rely on a global index, the MSCI world. Row 1 of Table 3.4 utilizes the MSCI-world index to calculate the cumulative average abnormal return. Exhibiting estimates of 0.59% (-1,1 window) and 1.02 (-2,5 window) the results remain positive and significant.

Table 3.4: Robustness Checks

Robustness Checks		
Modification	CAR[-1,1]	CAR[-2,5]
1. Global Index	0.59** (0.29)	1.02*** (0.48)
2. Conventional Bonds	-0.14 (0.25)	-0.38 (0.40)
3. Prior Information	0.37 (0.53)	0.86 (0.86)
4. BMP-Test Z Statistic	3.22***	2.06**
5. (-2, 5) Confounding Effects	0.66** (0.34)	0.92* (0.56)

*Table 3.4 presents several robustness checks. First, instead of using domestic market indexes a global market index, which is the MSCI world is used. The second modification collects conventional bond announcements for all SLB-issuing firms between 2020 and 2023. The third row investigates whether firms exhibit abnormal returns in the course of announcements at capital market days, through investor calls or by publishing a sustainable finance framework in advance to the intention of issuing SLBs in near future. Next, the fourth row shows the test statistic of a BMP-test accounting for event-introduced variance potentially affecting the efficiency of the market model's residual estimation. Finally, in the last row, confounding events are controlled over a longer event window of (-2, 5). *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.*

Second, I analyze the stock market reaction to conventional bond issuance by filtering out which SLB-issuers had also issued conventional bonds in the period between 2020 and 2023. The results of the market model estimation confirm leading contributions of the 1980's literature: The price reactions to conventional debt offerings are "no-news" events and slightly negative (Eckbo, 1986; Mikkelsen and Partch, 1986). Since some issuers have published a sustainable finance framework statement preceding the actual announcement day of the bond issuance,²⁹ I collected all media-event dates on which the broader mar-

²⁹For instance, on the 29th November 2021 the Italian energy company Snam S.p.A. released its finance frameworks that announces the issuance, updates the sustainable strategy over the next years and calibrates the sustainable performance target which the SLB is considered to achieve. The announcement date of the SLB issuance with its sustainable strategy and the final terms of pricing was on the 12th of January.

ket got informed about the intention of SLB-issuance and the updated (medium)-term sustainable target linked to the SLB. 40 companies have expressed their intention to issue ESG-related debt soon through media-statements, investor presentations or capital market days. The third row of Table 3.4 shows the results of the market model using the media-event dates. The cumulative abnormal returns both over the $(-1,1)$ and the $(-2,5)$ event window are statistically insignificant indicating that the market does not seem to price the mere announcement that a bond is being placed in the next few weeks. It can be assumed that the market anticipates the issue of SLBs to a certain extent in advance, however, only the announcement day - on which it is communicated exactly which targets from the financing framework are to be achieved, what the penalty will be in the event of non-achievement and how bond-specific criteria such as the maturity, the size of the coupon, the issue price or the issue yield will turn out - is associated with significant and positive abnormal returns.

Since the results of the t-test which estimates the residual standard error over the estimation period could possibly not adequately model event-induced variance (although the cumulative standard error is adjusted for the length of the event window) another parametric test is applied: the Boehmer, Masumeci and Poulsen (BMP) test. This test is performed to tackle event-induced heteroskedasticity resulting in biased standard-error estimations. This test first standardizes the abnormal returns by adjusting the residual standard deviation for a forecast error and in a second step utilizing the cross-sectional variance in the event period to form the test (Boehmer, Masumeci and Poulsen, 1991). Under the BMP test, the results of the market model remain significant for both event windows.

Finally, confounding events are controlled over a longer event window of $(-2, 5)$ reducing the sample size to 89. The cumulative abnormal returns remain positive and significant (0.66 % and 0.92%) for the respective event windows comparable to the results of table 3.1.

3.7 Conclusion

Recent years witnessed soaring growth of ESG-related debt instruments. The most recent ones are Sustainability-Linked Bonds through which issuers committing to future improvements. The innovation of SLBs is a penalty mechanism, which materializes if a predefined sustainable performance target is not achieved, endowing the investor with an instrument that makes the issuer liable. This raises the fundamental question of how different market participants will react to the issue of these bonds.

By doing an event study around the announcement day of SLBs, I show that the stock market reacts positively to the issuance. The results are positive and statistically significant over the $(-1, 1)$ and the $(-2, 5)$ event window. Moreover, the highest abnormal return of 0.32% is observable on the event day (0 event day). The issuance of SLBs generates shareholder value in the short-term after the issuance. Two main drivers of the positive announcement returns have been examined: first, the penalty mechanism of the SLBs does not explain the variation in abnormal returns. Contrary, SLBs with a penalty above the median exhibit higher abnormal returns. I interpret these findings that the market anticipates issuers to set targets they are most likely to achieve, as Kölbel and Lambillon (2022) suggest by finding no relationship between the penalty step-up and the sustainability premium. Second, the positive market reaction can be partially explained by a signaling argument as for green bonds (Flammer, 2021). Those companies that align their SLB-issuance with targets of the SBTi are associated with higher stock returns. Finally, those SLBs that are subsidized by a premium to the benefit of the issuer do not exhibit significantly higher abnormal returns, in contrast the wealth transfer argument from bond- to shareholders.

Future studies could investigate more intensively which factors explain positive or negative announcement returns of SLBs. Currently, it is difficult to assess the credibility and the ambitiousness of each target separately. As for green bonds, there should be certifications by independent third parties how strongly the targets are aligned with sector-specific pathways to achieve net-zero carbon emissions, a project to which the CBI committed itself to (CBI, 2024).³⁰ Another interesting research avenue would be to examine how the market reacts to the information that the issuer most likely fail to achieve the sustainability target.

³⁰Yet, there are second party opinions from companies like Sustainalytics or Vigeo Eiris that examine the quality of the target and verify the performance against the target. However, they have different assessment standards.

Appendix B

B.1 Performance of the Market Model Over the Estimation Period

This appendix section covers the in-sample fit of the market model and tests the statistical assumptions underlying the market model. After discussing goodness of fit measures, a bunch of statistical tests assess the statistical adequacy of the model. Moreover, it is shown that cross-sectionally the cumulative abnormal returns are asymptotically normally distributed although many individual securities abnormal return depart from normality. Finally, the statistical power is examined.

The table B.1.1 below plots the average alpha and beta parameters, the average R^2 and the average residual standard deviation across the 135 individual regressions over the event window for both two different market returns: the MSCI-world and the home country index on which the stock of the SLB-issuing firm is listed.

Table B.1.1: OLS Performance over Estimation Window

Variable	MSCI Index	Country Index
Alpha	-0.000	0.000
Beta	0.628	0.887
R2	0.142	0.317
Residuals	0.018	0.016

Table B.1.1 plots the average alpha, beta, R^2 and residual standard deviations of 135 individual time-series regressions over the 250-day estimation window by using either the MSCI world or county-related stock prices as market return. Each regression is estimated as $R_{i,t} = \alpha_i + \beta_i \times R_{m,t} + \epsilon_{i,t}$. The average R^2 across the sample is calculated as: $R^2 = \frac{1}{N} \sum_{i=1}^N R_i^2$. Similarly, the average alpha and beta parameters across the sample are calculated as $\bar{\alpha} = \frac{1}{n} \sum_{i=1}^n \alpha_i$ and $\bar{\beta} = \frac{1}{n} \sum_{i=1}^n \beta_i$. The residuals are the average residual standard deviation across the sample.

Overall, the two market indexes exhibit some differences: the average beta parameter of the country indices is slightly higher than the MSCI world (0.887 vs. 0.628). Moreover, country-related indices reduce the standard deviation of the abnormal returns to a greater extent than the MSCI-World Index leading to an increased ability to detect event effects: The higher the R^2 the greater is the variance reduction of the abnormal return, and the larger is the gain (MacKinlay, 1997). The estimation of the market model of

equation (1) via OLS is based on several statistical assumptions. The parameter estimations of α_i and β_i are consistent if the residuals (i.e., the abnormal returns) $\epsilon_{i,t}$ are identically and independently distributed and have a constant variance which would provide a consistent abnormal return estimation $AR_{i,\tau}$ over the event period. Additionally, the assumption that the estimation period residuals are normally distributed ensures that the least squares estimators are asymptotically efficient and have a minimum variance (Coutts et al., 1994).

Table B.1.2 below displays marginal significance for each of the 135 estimated equations.

Table B.1.2: Regression Diagnostics

Test	p<0.05	p>=0.05	Total
JB-Test	129	6	135
White-Test	35	100	135
BG-Test	19	116	135
DW-Test	20	115	135
GFT	4	131	135
FTest	22	113	135

Table B.1.2 displays several misspecification test for the individual securities OLS-regressions. The JB-Test is the Jacque-Bera Test assessing normality of the residuals. The White Test examines whether the residuals' variance is constant. Both the BG (Breusch-Godfrey) and the DW (Durbin-Watson) test for autocorrelation of order 1 of the residuals. The GFT and the F-test examine the parameter stability.

The OLS assumption that the residuals are normally distributed is most strongly violated as the Jacque-Bera test indicates. For nearly all (i.e. 129) residuals, the null hypothesis that the abnormal returns match a normal distribution is rejected (i.e. the p-value is below 0.05 threshold). Moreover, a White test indicates that 35 residuals do not have a constant variance, but are heteroskedastic. In contrast, the results of both the Durbin-Watson test and the Breusch-Godfrey test for autocorrelation of the residuals suggest that serial correlation is negligible (20 residuals exhibit first-order serial order correlation). Another assumption of the event study method is the parameter stability over both the estimation and the event period. Lack of beta-stability implies that that the concept of equilibrium returns is questionable and consequently the calculation of abnormal returns is meaningless (Coutts et al., 1994). I apply two different test to examine parameter stability: the first is a generalized fluctuation test, i.e. the Recursive Cumulative Sum (CUSUM) test which assesses the stability of the estimated parameters over time, while the second test, i.e., the F-Test (Chow-Test) tests for structural breaks in the regression coefficients. While the CUSUM test rejects the null hypothesis of parameter stability in

only 4 cases, the F-test finds structural breaks in 22 of the regression equations.

Although the results of table B.1.2 indicate that the market model has some misspecifications, especially in the assumption that the residuals (abnormal returns) are normally distributed, it is common sense in academic literature that both raw and abnormal returns of an individual stock depart from normality as they are fat-tailed (Fama, 1976; Brown and Warner, 1985). Brown and Warner (1985) show that the distribution of abnormal returns asymptotically converges to a normal distribution in the cross-section as it would be expected under the central limit theorem. Therefore, I test whether the abnormal returns of the (-1,1) event-window are cross-sectionally normal distributed.

Table B.1.3 test the cross-sectional security convergence to normality over the (-1, 1) event window. All three normality tests, i.e. the Shapiro-Wilk test, the Jarque-Bera test and the Kolmogorov-Smirnov test fail to reject normality. Consistent with Brown and Warner (1985), the cross-sectional abnormal returns do not depart from normality and standard parametric tests for the significance of cumulative average abnormal returns can be applied.

Table B.1.3: Statistical Test Results

	Test	Test_Statistic	P_Value
W	Shapiro-Wilk	0.98	0.11
JB	Jarque-Bera	5.73	0.06
D	Kolmogorov-Smirnov	0.06	0.63

The Shapiro-Wilk, the Jarque-Bera and the Kolmogorov-Smirnov test examine the normality of cross-sectional cumulative abnormal returns over the (-1,1) event-window.

Finally, the power of the test is evaluated. In an event study setting a high power is associated with a high probability of correctly rejecting the null hypothesis (of no cumulative abnormal return) when CARs are indeed present. The table below specifies the level of abnormal returns (0.6% over the -1,1 event window), the average cumulative standard deviation (0.026) and the sample size. Overall, the power of the test has an acceptable size of 75.8%.

Table B.1.4: Power of One-Sample t-Test

Parameter	Value
Sample Size	135
Delta	0.006
Standard Deviation	0.026
Power	0.758

Table B.1.4: Power of One-Sample t-Test

Table B.1.4 depicts the power of the test for a given level of abnormal return, sample size and standard deviation over the (-1,1) event window. The power is reported for a two-sided test with a significance level of 5%. The standard deviation is the average residual standard deviation across firms.

B.2 Statistical Tests

This appendix gives details of the procedures and statistical assumptions used for statistical inference. The section basically follows the notations in MacKinlay (1997).

B.2.1 Basic Statistical Assumptions and t-Test

The market model is defined as:

$$R_{i,t} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{3.6}$$

This model is estimated using ordinary least squares regression under the return normality assumption, where:

$$\begin{aligned} E(\varepsilon_{it}) &= 0 \\ \text{Cov}(\varepsilon_{it}, \varepsilon_{iKt}) &= \begin{cases} 0 & \text{if } i \neq k \\ \sigma_i^2 & \text{if } i = k \end{cases} \end{aligned} \tag{b}$$

Also, $\text{Cov}(\varepsilon_{it}, R_{mt}) = 0$ for all t and i .

The estimated parameters $\tilde{\alpha}_i$ and $\tilde{\beta}_i$ are used to define an out-of-sample prediction error (i.e., an abnormal return) over the event period $\tau = \tau_1, \tau_2$ as:

$$AR_{i\tau} = R_{i\tau} - (\tilde{\alpha}_i + \tilde{\beta}_i R_{m\tau}) \quad (3.7)$$

Under assumptions 1(a)-1(c), the abnormal returns $AR_{i\tau}$ are distributed as follows:

$$E(AR_{i\tau}) = 0 \quad (2a)$$

$$\text{Cov}(AR_{i\tau}, AR_{is}) = \begin{cases} 0 & \text{if } \tau \neq s \\ \sigma_i^2 & \text{if } \tau = s \end{cases} \quad (2b)$$

$$\text{Cov}(AR_{i\tau}, R_{m\tau}) = 0$$

$$\text{Cov}(AR_{i\tau}, AR_{j\tau}) = \begin{cases} 0 & \text{if } i \neq j \\ \sigma_i^2 & \text{if } i = j \end{cases}$$

These conditions imply that the abnormal returns are serially and cross-sectionally uncorrelated.

The individual securities' abnormal returns are aggregated over the event window τ ranging from τ_1 to τ_2 , defining the cumulative abnormal return as:

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i,\tau} \quad (3.8)$$

The variance of the cumulative abnormal return is given by the disturbance variance of the market model over the event window times the length of the event window:

$$\sigma_i^2(\tau_1, \tau_2) = (\tau_2 - \tau_1 + 1) \tilde{\sigma}_\varepsilon^2 \quad (3.9)$$

Under the null hypothesis H_0 , the distribution of the cumulative abnormal return is:

$$CAR_i(\tau_1, \tau_2) \sim \mathcal{N}(0, \sigma_i^2(\tau_1, \tau_2)) \quad (3.10)$$

For cross-sectional inference, the daily average abnormal return \overline{AR}_τ for each event period and the cumulative average abnormal return \overline{CAR} over the event window $\tau = \tau_1, \tau_2$ are

defined as:

$$\begin{aligned}\overline{AR}_\tau &= \frac{1}{N} \sum_{i=1}^N AR_{i\tau} \\ \text{var}(\overline{AR}_\tau) &= \frac{1}{N^2} \sum_{i=1}^N \tilde{\sigma}_\varepsilon^2 \\ \overline{CAR}(\tau_1, \tau_2) &= \frac{1}{N} \sum_{i=1}^N CAR_i(\tau_1, \tau_2) \\ \text{var}(\overline{CAR}(\tau_1, \tau_2)) &= \frac{1}{N^2} \sum_{i=1}^N \tilde{\sigma}_i^2(\tau_1, \tau_2)\end{aligned}$$

Under the null hypothesis, the distribution of the cumulative abnormal returns is:

$$\overline{CAR}_i(\tau_1, \tau_2) \sim \mathcal{N}(0, \text{var}(\overline{CAR}(\tau_1, \tau_2))) \quad (3.11)$$

A standard t-test procedure adjusting the estimated standard error is defined as:

$$t_{\overline{CAR}} = \frac{\overline{CAR}(\tau_1, \tau_2)}{\sqrt{\text{var}(\overline{CAR}(\tau_1, \tau_2))}} \quad (3.12)$$

The distributional result is asymptotically normal with respect to the number of bonds included and the length of the estimation window.

B.2.2 The BMP-Test

There are several potential problems in hypothesis testing relying on the assumptions in Section B.2.1. The time-series properties of daily data are not independent across time, nor is the cross-sectional independence assumption realistic (Brown and Warner, 1985). However, as regression diagnostics indicate, serial correlation among the abnormal returns seems to be a minor problem, as is cross-sectional correlation since the event-windows of the issuing firms rarely overlap.

A more significant issue is that abnormal return parameters tend to have greater variance during the event period than in the estimation period (Boehmer, Masumeci, and Poulsen, 1991).

³⁰¹ Note that one could also cluster over calendar days, where the average abnormal returns are aggregated over the event window period as of $\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau_1}^{\tau_2} \overline{AR}_\tau$. Kolari, et al. (2018) utilize the clustering approach over firms and event days to derive serial and cross-correlation robust standard errors.

Therefore, these authors constructed a standardized t-test that adjusts for event-induced variance and cross-sectional correlation in the abnormal returns over the event window.

First, the cumulative abnormal returns of each issuer i are standardized as:

$$SCAR_i = \frac{CAR_i}{\sigma_\varepsilon^2 \left[k + \frac{k}{T} + \frac{(R_{m\tau} - \bar{R}_m)^2}{\sum_{\tau=1}^T (R_{m\tau} - \bar{R}_m)^2} \right]} \quad (3.13)$$

where T is the length of the estimation window, k is the length of the event window, $\bar{R}_m = \frac{1}{T} \sum_{\tau=1}^T R_{m\tau}$ is the average market return of the estimation window, and σ_ε^2 is the estimated variance from the market model regression. The denominator $\sum_{\tau=1}^T (R_{m\tau} - \bar{R}_m)^2$ is the variance of the market return over the estimation period.

To allow for event-induced variance changes, the standardized abnormal returns are divided by the cross-sectional standard error, and the BMP-test evolves as:

$$t_{BMP} = \frac{SAR_{i\tau}}{\sqrt{\frac{1}{N^2} \sum_{i=1}^N (CAR_i(\tau_1, \tau_2) - \bar{CAR}(\tau_1, \tau_2))^2}} \quad (3.14)$$

B.3 Cross Sectional Regression with different ESG-proxies

This section corresponds to the cross-sectional regression of section 3.5.2. Since the ESG-combined score does not explain the variation in abnormal returns, the absence of significance can either imply that the ESG-combined score is not an appropriate measure or the signaling argument is not as strong as hypothesized. To explore this further, alternative ESG performance proxies were collected from Refinitiv’s Sustainability Dashboard, which provides more specific environmental metrics, including the Emission Score, Resource Use Score, annual change in Scope 1 and Scope 2 emissions, annual change in emission intensity, and proportion of green revenue. Appendix Table B.3.1 below incorporates various proxies for the environmental performance of SLB-issuing companies. Column 1 replaces the ESG-combined score with the Environmental Score, which focuses exclusively on environmental aspects. The coefficient remains insignificant, suggesting that this broader environmental measure does not correlate with cumulative abnormal returns. Column 2 adds a dummy variable equal to 1, if the emission intensity reduction of scope 1 and scope 2 emissions has been in the highest sample quintile prior to the issuance. While this variable remain insignificant, firms in the top quintile for emission intensity reduction do show a positive, albeit modest, association with abnormal returns, indicating that substantial emission reductions lead to a more higher stock returns at SLB announcement date.

Column 3 reintroduces the ESG-combined score and shows that the Science-Based Target Initiative (SBTi) commitment remains positively and significantly associated with abnormal returns. Additionally, a new dummy variable indicating SLBs with Scope 3 emission reduction targets has been included. Scope 3 greenhouse gas emission targets are considered more ambitious, as they cover indirect emissions not directly controlled by the issuer (in contrast to Scope 1 and Scope 2 emissions). Given that Scope 3 emissions comprise the majority of global greenhouse gas emissions, incorporating them in SLBs could signal a heightened commitment to emission reductions. Although positively associated with cumulative abnormal returns—suggesting that more ambitious, comprehensive emission targets may drive a favorable market response—this effect does not reach statistical significance.

The insignificance of broader ESG measures may be due to their backward-looking nature, capturing prior performance rather than the forward-looking commitments inherent to SLBs. However, it appears that traditional ESG scores and prior emissions reductions do not fully capture the market’s response to SLB issuance, which is likely more sensitive to future-oriented, bond-specific sustainability targets.

Table B.3.1: Cross-Sectional Regression with Different ESG Measures

Dependent Variable:	CAR (-1, 1)		
Model:	(E-Score)	(2)	(3)
<i>Variables</i>			
StepUpPenaltyYes	-0.006 (0.007)	-0.006 (0.007)	-0.010 (0.007)
High Penalty	0.004 (0.007)	0.003 (0.007)	0.004 (0.007)
SBTi	0.008 (0.006)	0.008 (0.006)	0.012* (0.007)
E-Score	0.000 (0.000)		
High Emission Reduction		0.010 (0.008)	0.007 (0.008)
ESG-Combined Score			0.000 (0.000)
Scope3 Emissions			0.008 (0.007)
Bond-specific variables	Yes	Yes	Yes
Firm-specific variables	Yes	Yes	Yes
<i>Fixed-effects</i>			
Sector	Yes	Yes	Yes
Country	Yes	Yes	Yes
<i>Fit statistics</i>			
Observations	120	119	115
RMSE	0.01596	0.01593	0.01540
Adjusted R ²	0.13283	0.13437	0.15637
F-test	1.4239	1.4260	1.4914

Appendix Table B.3.1 extends the Cross-Sectional Regression depicted in table 3.3. The dependent variable is the cumulative average abnormal return (CAR) over the (-1, 1) event window. The first column uses an Enviromental Score instead of an ESG-Combined Score. Step-Up Penalty is a dummy equal to 1, if the penalty mechanism is a coupon-step-up, and zero otherwise. SBTi is equal to 1, if the issuing firm has committed to science-based targets prior to the SLB-issue, and zero otherwise. The second column add an emission reduction variable that is equal to 1, if the issuer has been in the highest

*quintile of emission intensity reduction of scope 1 and scope 2 emission prior to the SLB issuance, and zero otherwise. Finally, column three adds scope 3 emissions which is equal to 1, if the sustainable performance target of the SLB includes a scope 3 emission reduction target, and zero otherwise. The bond-specific variables (Coupon, Maturity and magnitude of the penalty) and the firm-specific variables (Total Assets, Leverage, EBITDA-Margin, Tobin's Q and Cash-Flow are also added. Heteroskedastic robust standard-errors are in parentheses, significant codes: ***: 0.01, **: 0.05, *: 0.1. .*

B.4 Yield Curve Estimation

To examine whether those SLB exhibiting a premium (implying that investors pay higher prices and therefore accept lower yield to the benefit of the issuer) are associated with higher cumulative abnormal returns in the aftermath of the SLB-issuance announcement, yield curves are fitted with the Nelson Siegel Svensson-Method (NSS) to infer (theoretical) yields over the bonds' remaining time to maturity spectrum by fitting yield curves for the SLB-issuing firm on the announcement day. Afterwards, the yield of the SLB at issuance is compared to the NSS-yield at the same residual maturity. If an SLB bond is below its yield curve this is evidence for a premium, as investors accept a lower yield. This is the same approach utilized in my first paper "The Pricing of Sustainability-Linked Bonds on the Primary and Secondary Bond Market."³¹

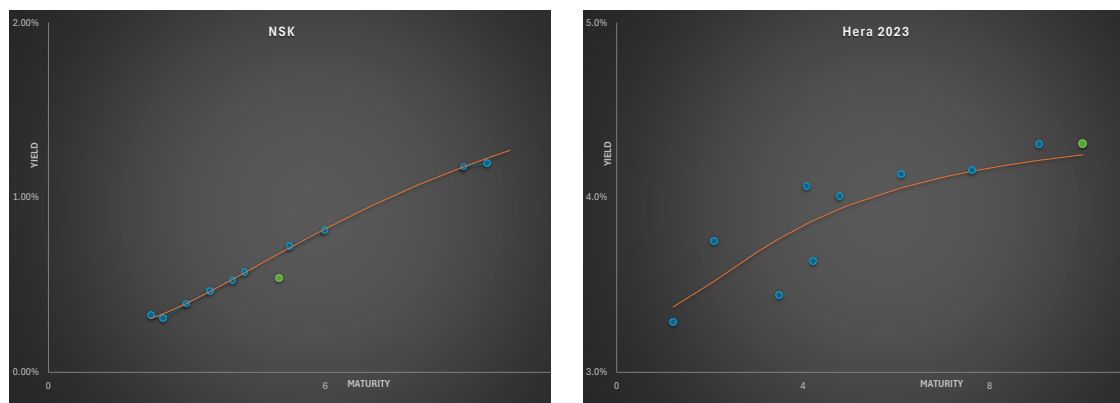


Figure B.4.1: Yield Curves estimated by Nelson–Siegel–Svensson method on the SLB-issuance date. The blue dots are the observed yields of the issuer’s conventional bonds that trade on the secondary market. A yield curve is fitted with the Nelson–Siegel–Svensson method. Finally, the SLB (green dot) is overlaid. A SLB below its curve implies a sustainable premium, or greenium.

³¹Since the methodology is identical to that of the first paper, I decided not to plot all yield curves again, as many are similar to those in the first paper. The curves are digitally attached (see folder “2 Paper/Code”).

4 Climate Risk Spillovers and Hedging with ESG Assets

Abstract

This paper examines the connectedness between climate risk—distinguishing between transition and physical risk—and financial asset returns, focusing on ESG-labeled bonds, equities, and conventional markets. Using a combination of generalized and quantile-based vector autoregressions, DCC-GARCH models, and dynamic portfolio analysis, the study shows that climate risk shocks propagate asymmetrically across asset classes. Transition risk transmits more strongly into bond markets, while physical risk impacts equities. ESG bonds, particularly green and sustainability-linked bonds, exhibit positive conditional correlations with transition risk and provide moderate hedging effectiveness during periods of elevated climate uncertainty. However, these assets offer limited protection against physical climate shocks. Clean energy equities fail to deliver consistent hedging benefits for either type of risk. The findings highlight the importance of distinguishing between risk types when designing climate-resilient investment strategies and call for the development of financial instruments better suited to hedge physical climate risks.

Keywords: Sustainable finance, Sustainability-linked bonds, Climate Risk

4.1 Introduction

Rising awareness of the economic and societal implications of climate change has intensified policymakers' and investors' focus on green and environmentally sustainable investments. Climate risk, typically categorized into physical risk—stemming from acute environmental events like floods or wildfires—and transition risk—arising from regulatory, policy, and technological shifts toward a low-carbon economy—poses significant challenges for financial stability. A survey by Krueger, Sautner and Starks (2020), shows that investors consider climate change as an important investment risk and already incorporate such risks into the investment decision process. Rather than divesting, investors consider active risk management strategies to mitigate climate-related risks. Following this, a relevant question is not just whether climate risk is fully priced in financial markets, but also how it transmits to asset classes—particularly ESG assets—and whether these assets can function as diversifiers, hedges, or even safe havens during periods of elevated climate risk.

Recent contributions investigate if transition risk, often proxied by a firm's carbon intensity, is priced in the cross-section of stock returns, as investors demand a carbon risk premium as compensation to hold stocks of carbon-intensive firms (Bolton and Kacperzyck, 2021; Hsu et al., 2023; Bats et al., 2024). This finding is echoed for the US bond market (Seltzer et al., 2022) and the European Bond market (Broeders et al., 2024). Flipping this argument, related contributions outline that climate friendly assets, like green bonds would offer lower expected returns in the cross-section of bond returns (Huynh and Xia, 2021; Bats et al., 2024), as investors pay higher prices (accept lower future returns) on assets that might perform better in times of heightened risk consistent with the intertemporal hedging demand theory (Merton, 1973).³²

A second strand of research examines shock spillovers and return connectedness between ESG and conventional assets, particularly during turbulent periods (e.g., Reboredo, 2018; Pham, 2021; Saeed et al., 2020). While these studies provide insights into diversification within and across asset classes, few explicitly address the interaction between climate risk shocks and the performance of ESG assets.

This study addresses an important gap in the literature by exploring how climate risk—both physical and transition—is connected to asset returns across ESG bonds, equities, and conventional financial instruments and if a stock portfolio can be hedged against

³²Often, risk is measured by constructing a climate change news beta, that captures a bond's covariance with the climate change news risk index (Engle et al., 2020, Huynh and Xia, 2021; Bua et al., 2024). Bonds, that have a higher covariance (higher beta) with the climate change news index perform better in times of elevated climate risk, therefore investors are willing to pay higher prices.

elevated climate risk. These dynamics offer indirect insight into climate risk pricing—as this study does not test directly whether climate risk is priced in the classical asset pricing sense³³—and into how climate risk interacts with financial markets and whether it is absorbed or amplified through asset price movements. In particular, this study asks:

1. What is the connectedness between ESG-related assets and unexpected changes in physical and transition climate risk? Are there any spillovers?
2. Does the connectedness vary under extreme conditions or in different tails of the distribution?
3. Do assets and climate risk co-move, and can risk be hedged by adding ESG assets to an unhedged stock portfolio in times of heightened climate risk?

To answer these questions, first the spillovers between climate risks and (ESG) assets are captured based on forecast error variance decompositions from vector autoregressions (Diebold and Yilmaz, 2012; Diebold and Yilmaz, 2014), and its extensions: the QVAR approach and the quantile-on-quantile (QQC) approach examining how shocks at the tail of the distribution affect the system. A DCC-GARCH model is then used to estimate the dynamic conditional correlations between assets and climate risk, building the groundwork for a portfolio analysis that tests whether ESG assets can hedge a stock portfolio in times of elevated climate risk.

Closely related to this study are Cepni et al. (2022), who show that green bonds positively co-move with climate risk and therefore serve as hedge instruments; Bouri et al. (2023), who show that climate risk has predictive power for next-day returns and volatility of brown and green assets and Cepni et al. (2023), who explore that spillovers between ESG assets decrease during periods of heightened climate risk, thereby improving diversification of an equity portfolio.

While using the same textual climate risk indicator developed by Bua et al. (2024), this study extends previous work by analyzing how tail shocks to climate risk affect asset connectedness differently, by exploring the hedging effectiveness of a novel ESG fixed-income instrument—Sustainability-Linked Bonds (SLBs)—and by applying a dynamic out-of-sample hedging portfolio strategy.³⁴

³³Classical asset pricing models would examine expected returns of exposure to a climate risk factor and test whether this exposure earns a significant risk premium.

³⁴Unlike the study of Cepni et al. (2023), this paper places climate risk—not the ESG vs- conventional asset linkage—at the center of the analysis, by examining how it transmits to ESG assets and whether these can function as climate hedges.

The findings contribute to two key areas:

1. The pricing of climate risk—albeit indirectly through transmission channels rather than risk premia.
2. The diversification and hedging properties of ESG assets.

First, when an average shock to series j hits the network, climate risk is a net receiver or absorber. However, at the tails of the distribution, climate risk can act as a net transmitter of shocks. Transition risk, in particular, strongly transmits shocks to ESG bond markets, while physical risk is more strongly connected to equities. Next, the DCC-GARCH model shows that ESG-related bonds exhibit positive conditional correlations with transition climate risk (but lower correlation for physical risk), indicating that they might protect a conventional equity portfolio in times of climate stress. This is confirmed by portfolio-analysis, showing that green and sustainability-linked bonds are most effective in hedging transition risk, but fail to hedge physical risk.

Therefore, ESG bonds might function as intertemporal hedges, assets that rise in value when climate risk intensifies, consistent with the theoretical framework provided by Pastor, Stambaugh and Taylor (2021) where green assets have lower expected return than brown assets, driven by a taste premium and a hedge premium, but outperform when ESG awareness of investors increase, or climate risk (unexpectedly) rises. This hedging behavior is not observed for other ESG assets such as clean energy stocks, likely due to their equity-like cash flow risk and greater exposure to physical climate shocks, consistent with Yousaf et al. (2022).

The remainder of this paper is structured as follows: Section Literature Review and Hypothesis review the related literature, stresses the contribution and posits hypotheses. The data section sums up the data gathering and descriptive statistics. The Methodology section is split into three parts and explains the variance forecast error decomposition to retrieve spillovers between different series, the DCC-GARCH model and the portfolio approach. Section 5 presents the results for each applied method. Next, a discussion interprets and puts the results into context before the last section concludes.

4.2 Literature Review, Hypothesis and Contribution

4.2.1 Related Literature

The expansion of sustainability-related assets has led to a boom in academic research.

This paper contributes to three main strands of the literature: (i) Climate Risk Spillovers and Hedging with ESG Assets properties of ESG-linked assets, (ii) the pricing of climate risk in financial markets, and (iii) the influence of climate risk regimes—particularly extreme physical and transition risk—on the connectedness between ESG assets and other financial markets.

A first strand investigates the relationship between ESG-related assets—particularly green bonds—and other markets/risk indicators by examining the net-connectedness with other assets such as bonds, commodities, oil, green and conventional equities.

Among the first studies is Pham (2016), who finds evidence of volatility clustering and volatility spillover between green bonds and the conventional bond market. Building on this, Reboredo (2018) and Reboredo et al. (2020) show that green bonds do not diversify a treasury or corporate fixed-income portfolio, instead, they are affected by price spillovers. In contrast, green bonds weakly co-move with stocks and clean energy, are less affected by spillovers, and offer diversification benefits. Reboredo and Ugolini (2020) advise holding green bonds to hedge downside risks from holding position ins stocks, clean energy or high yield debt.

Subsequently, a growing number of studies have examined climate risk spillovers and the hedging effectiveness of green bonds, climate-friendly stocks, clean energy, and commodities during both normal and turbulent market phases, applying different methods such as wavelet coherence (Nguyen et al., 2021), copulas and value-at-risk (Liu et al., 2021; Reboredo, 2018), cross-quantilogram (Pham, 2021; Pham and Nguyen, 2021; Bouri et al., 2023), net connectedness measures based on forecast error variance decomposition (Jin et al., 2020; Pham and Cepni, 2022; Reboredo et al., 2020; Chatziantoniou et al., 2022), or DCC-GARCH and portfolio analysis (Dutta et al., 2021; Saeed et al., 2020; Yousaf et al., 2022).

Consistent with Reboredo (2018), Nguyen et al. (2021) and Pham (2021) both find that green bonds and green stocks are weakly dependent in normal times so there are diversification benefits, but during financial turmoils spillovers between them increase and hedging fails, as they boom and bust together.³⁵

Liu et al. (2021) find that green bonds and clean energy stocks do not serve as effective hedges for one another, as evidenced by the presence of positive and asymmetric risk spillovers in both directions, particularly during market downturns. Saeed et al. (2020)

³⁵This would be the "classical" definition of a good hedge and stands in contrast to mine that a good hedge of climate risk should be positively correlated to it. The returns between two assets should be negatively correlated, especially during market downturns. Therefore, a negative equity shock leads to flight to quality like green bonds and a negative return spillover.

determine if clean energy and green bonds can hedge oil prices and energy stocks and find that clean energy stocks serve as a better hedge than green bonds. Jin et al. (2020) show that the connectedness between carbon future returns and green bonds is the highest, they positively commove and green bond effectively hedge carbon risk. Spillovers are small but positive between green bonds and investor attention - proxied by Google Search Volume Index and Bloomberg Terminal news - and increase at extreme quantiles, indicating tail dependence and therefore, attention is determined by green bond performance (Pham and Cepni, 2022).

A related question is if sustainable assets have been a hedge or safe haven asset during the Covid-19 pandemic. Yousaf et al. (2022) show that green bonds are weak safe haven assets to S&P 500 downturns and had superior risk-reduction and return performance during the pandemic. Dutta et al. (2021) show that climate bonds do not move in the same direction as the S&P500 and therefore might hedge downside risks it, although the hedging effectiveness deteriorated during the pandemic. Spillovers spiked between all conventional and green investments (Arif et al., 2021), despite this higher spillovers during Covid, Naeem et al. (2021) find diversification of green bonds.

Beyond the connectedness and spillover-based analyses, another body of work examines whether climate risk is priced in asset markets by verifying if transition risk - in terms of carbon emissions (or carbon intensity) - of a firm is priced in the equity market applying classical asset pricing tests.³⁶ Bolton and Kacperczyk (2021) show that carbon risk is priced in the cross-section of stock returns, supporting evidence for a carbon risk premium: to bear the additional carbon/ transition risk, carbon-intensive companies must deliver higher expected returns, confirmed by Hsu et al. (2023) and Bats et al. (2024).

Contrary, In, Park and Monk (2019) find evidence that a portfolio that is long on low carbon emissions stocks and short of high emission stocks generates positive alpha (abnormal returns), supported by Sun et al. (2021) who claim investors showing limited attention to physical climate risk (drought) and a trading strategy longing (shorting) stocks with low (high) exposure to climate change generates positive factor adjusted alphas of 7%. For the US bond market Seltzer et al. (2022) and, for the European Bond market, Broeders et al. (2024) also find evidence of a carbon risk premium. Flipping this argument, recent contributions outline that climate friendly assets hedging climate risk, like green bonds,³⁷

³⁶Generally, these studies either apply panel regressions (Bolton and Kacperczyk, 2021) or asset pricing models, like (univariate) portfolio sorting to compare raw returns of green and brown portfolios, Fama-French factor modeling to test if the return difference is risk-adjusted and Fama-MacBeth regressions to check if greenness is a priced risk factor across firms. (e.g., Hsu et al., 2023)

³⁷Often, risk is measured by constructing a climate change news beta, that captures a bond's covariance with the climate with the climate change news risk index (Engle et al., 2020; Huynh and Xia, 2021; Bua et al., 2024). Bonds that have a higher covariance (higher beta) with the climate change news index perform better in times of elevated climate risk, therefore investors are willing to pay higher prices.

would offer lower expected returns in the cross-section of bond returns (Huynh and Xia, 2021; Bats et al., 2024), as investors pay higher prices (accept lower future returns) on assets that might perform better in times of heightened risk consistent with the intertemporal hedging demand theory (Merton, 1973). In contrast, Duan et al. (2023) find lower returns for carbon-intensive US-bonds and higher returns for greener bonds, which might be driven by a shift of investors' ESG preferences—due to rising environmental awareness—as Pastor, Stambaugh and Taylor (2021) theoretically model. According to this seminal model, assets affected by climate risk should offer higher expected returns to compensate investors for taking risk. However, investor preferences may shift toward ESG assets, which therefore outperform during periods of heightened climate risk.

Finally, novel literature utilized textual risk measures of climate risk (Cepni et al., 2022; Cepni et al., 2023; Bouri et al., 2023) and how this might affect spillover between conventional and different ESG-assets (Cepni et al., 2023), the return and volatility predictability of "brown" and "green" investments (Bouri et al., 2023) and the hedging and diversification benefits of ESG investments for a conventional stock portfolio under different regimes of climate risk (Cepni et al., 2022; Cepni et al., 2023). Particularly green bonds can hedge an equity portfolio (Cepni et al., 2022), especially when transition risk is high, while ESG equity should be utilized as a diversification tool against climate risk. In addition, shock transmission between the conventional stock market and ESG assets is lower during periods of high climate uncertainty, emphasizing their diversification benefits (Cepni et al., 2023).

This paper contributes primarily to the first and third strands. While the second strand applies classical asset pricing models to test whether climate risk earns a premium, this study takes a complementary approach—examining how climate risk transmits to ESG assets using advanced connectedness and quantile spillover models following Chatziantoniou et al.(2021) and Gabauer and Stenfors (2024). Second, this study evaluates which assets can hedge or diversify equity portfolios during periods of heightened climate risk. Thereby, this is the first study that examines the hedging effectiveness of a novel ESG fixed income instrument—SLBs—by applying an out-of-sample portfolio strategy, offering practical relevance for real-world investors.

Together, these contributions position the study at the intersection of ESG asset pricing, climate risk transmission, and real-world portfolio management.

4.2.2 Hypothesis

Based on the academic literature, the study’s hypotheses are:

Hypothesis 1: Climate Risk Transmission

Unexpected changes in climate risk (both physical and transition) transmit to ESG asset markets through significant spillovers and dynamic connectedness, particularly during high-risk periods.

Recent studies using quantile-based spillover models (Pham and Çepni, 2022; Bouri et al., 2023) find that spillovers between climate-related and ESG assets intensify under extreme market conditions. This study builds on these insights by focusing specifically on the transmission of unexpected climate shocks to ESG markets across different climate risk regimes.

While not a direct asset pricing test, this hypothesis is closely related to the classical climate risk pricing literature (e.g., Bolton and Kacperczyk, 2021; Hsu et al., 2023), which evaluates whether climate risk is reflected in expected returns. If climate risk were fully priced, markets would likely absorb such shocks with limited impact on ESG asset dynamics. However, large spillovers during climate stress events may indicate that markets respond reactively to new information—suggesting that climate risk is only partially priced or that investor attention is time- or state-dependent (In, Park and Monk, 2019; Sun et al., 2021). This paper offers complementary evidence by testing whether climate shocks, particularly in the tails of the distribution, significantly affect ESG asset behavior.

Hypothesis 2: Hedging Properties of ESG Bonds

ESG bonds—especially green and sustainability-linked bonds—can hedge climate risk in conventional equity portfolios.

This hypothesis is motivated by the intertemporal hedging framework of Merton (1973) and the theoretical model of Pastor, Stambaugh, and Taylor (2021), which predicts that green assets may outperform during periods of rising ESG preferences or unexpected climate shocks. If ESG bonds serve as effective climate hedges, they should exhibit positive conditional correlations with climate risk during high-risk periods and improve portfolio performance when climate-related uncertainty increases.

Hypothesis 3: Asset Class Heterogeneity

Clean energy equities are less effective as climate hedges compared to ESG bonds, due

to their higher exposure to market volatility and physical climate shocks. In contrast, the safer nature of offered future cash-flows of (ESG) bonds would offer more effective diversification benefits. This hypothesis is grounded in findings from Yousaf et al. (2022) and reflects the idea that ESG equities may behave more like conventional risky assets under stress, reducing their hedging effectiveness during extreme climate events.

4.3 Data and Statistics

This study relies on two primary datasets: one covering financial asset prices and the other providing climate risk indicators. The sample period spans from November 1, 2021, to June 28, 2024, based on data availability. All financial data are sourced from Refinitiv, and daily log returns are used throughout the analysis.

The financial dataset includes daily closing prices for a range of European equity and bond indices that reflect both conventional markets and ESG-related investments: The development of the conventional stock market is tracked by the Stoxx 600, which covers the companies with the highest market capitalization. Its sustainable counterpart, the Stoxx Europe 600 Sustainability Index (Stoxx-Sus in the following), selects components according to their sustainability rating and overweight leaders. The WilderHill Clean Energy Index reflects firms involved in renewable energy and decarbonization initiatives. Gold is added to the sample due to its safe haven status in times of financial turmoil (e.g., Yousaf et al., 2022). For fixed-income markets, three bond indices are selected from iBoxx, covering a range of different bond indicators globally. In particular, the iBoxx Euro Sustainability-Linked Bond Index, the iBoxx Euro Green Bond index (GB) and the iBoxx Euro Corporate index (CB) with seven to 10 years remaining maturity are selected. While the indices cannot be exactly matched on criteria such as modified duration, they all track investment-grade, euro-denominated corporate bonds.

The second data set includes daily climate risk indicators covering both physical and transition risk. Recent contributions have quantified climate risk via textual analysis of news (Engle et al., 2020; Bua et al., 2024; Faccini et al., 2023; Ardia et al., 2023). The seminal work of Engle et al. (2020) constructs a climate-related vocabulary based on authoritative reports and applies term frequency-inverse document frequency (TF-IDF) to rank the importance of these terms. To measure climate risk exposure in financial markets, cosine similarity is used to compare daily news articles against this vocabulary, generating a daily climate concern series. In this framework, no news is good news:

increased climate coverage corresponds to heightened market concern.³⁸

Similarly, Bua et al. (2024) extend this approach by distinguishing between Physical Risk (PRI) and Transition Risk (TRI), constructing separate vocabularies to capture distinct sources of climate-related risks. To isolate unexpected changes in climate risk, residuals from an AR(1) model are used, provided by Bua et al. (2024). These residuals remove predictable variation and capture shocks in climate risk perception. Following recent studies (Cepni et al., 2022; Bouri et al., 2023; Cepni et al., 2023), these residuals are used in all subsequent analysis.

Appendix Figures C.1.1 and C.1.2 plot the residual-based indicators of transition and physical risk alongside the returns of the asset series. Notably, transition risk peaks around April 2024, while physical risk is most volatile during mid-2022. Regarding asset returns, heightened volatility is observed in 2022, coinciding with rising inflation and interest rates. As expected, bonds exhibit lower volatility than stocks, while gold had some stronger periods of gains especially by the end of 2023 and 2024.

Table 4.1 below presents summary statistics and diagnostic tests of the two climate risk measures and the assets returns. The highest average returns are reported for gold (0.038%) and for the Stoxx 600. Conversely, the Wilderhill Clean Energy index has the worst risk-return relationship of all assets. The three bond indices green bonds, SLBs and conventional bonds have the lower average returns than the two Stoxx indices and gold but also have the lowest risk (standard deviation).

³⁸Extending the measurement of climate risk, Faccini et al.(2023) apply Latent Dirichlet Allocation (LDA), a machine-learning-based topic modeling approach, to classify Reuters news into four climate risk categories: Natural Disasters, Global Warming, International Summits, and U.S. Climate Policy. This method avoids predefined dictionaries, allowing for a more granular, data-driven decomposition of climate risk. Instead of just tracking climate-related news volume, Ardia et al. (2023) construct a Media Climate Concerns Index that combines risk intensity, sentiment polarity and unexpected climate shocks.

Table 4.1: Descriptive Statistics and Diagnostic Tests

Series	Mean	StdDev	Skewness	Kurtosis	Jarque-Bera	Ljung-Box	ADF
Transition Risk	0.0003	0.025	-0.068	0.375	4.826*	77.899***	-6.957**
Physical Risk	-0.002	0.022	0.594	1.215	84.557***	50.876***	-6.269**
Stoxx	0.009	0.913	-0.283	2.679	219.380***	13.251	-8.528**
Stoxx_Sus	0.007	0.905	-0.071	2.634	203.659***	12.125	-8.545**
Clean Energy	-0.219	2.787	0.290	0.393	14.479***	12.388	-8.221**
Green Bonds	-0.029	0.440	0.293	1.568	82.287***	11.596	-8.072**
SLBs	-0.028	0.434	0.233	1.779	99.218***	27.049***	-7.884**
Gold	0.038	0.859	0.014	1.419	59.271***	14.874	-8.637**
Corporate Bonds	-0.028	0.488	0.353	1.637	93.207***	22.146**	-7.985**

Table 4.1 shows descriptive statistics and diagnostic tests for the two climate risk indices and the returns of the financial series. The Jarque-Bera test assesses normality, the Ljung-Box test checks for autocorrelation, and the ADF denotes the Augmented Dickey-Fuller test for unit roots. Significance levels are indicated as follows: *** for 1%, ** for 5%, and * for 10%.

4.4 Methodologies

The empirical part is based on three different approaches. First, to measure the connectedness between (ESG)-related assets and an (unexpected) change in climate risk, a generalized vector autoregressive (VAR) framework is employed which measures shock spillovers between the series. Second, a dynamic conditional GARCH (DCC-GARCH) model is utilized to retrieve conditional correlations between climate risk and (ESG) assets. Finally, a forward-looking, climate risk hedged portfolio is constructed.

4.4.1 Net Connectedness

Spillover (or net connectedness) is about how a shock to Climate Risk's innovations (error terms) explains the forecast error variance of (ESG)-related assets (and vice versa).

The connectedness between asset returns and unexpected climate risk is examined using the seminal approach by Diebold and Yilmaz (2012). They establish a spillover measure in asset returns based on forecast error variance decomposition from a generalized vector autoregression (VAR) invariant of variable ordering, to quantify the impact shocks in a

system have on each other.³⁹

Diebold and Yilmaz (2012) emphasize that financial shocks are naturally correlated and move together, and their framework captures this interconnectedness without requiring order-dependent decompositions. Stronger connectedness among variables implies greater comovement and may indicate financial contagion.

Numerous recent studies rely on the Diebold and Yilmaz approach (2012, 2014) to measure spillovers among variables (e.g., Ferrer et al., 2021), identifying leading indicators that influence other markets (e.g., Reboredo and Ugolini, 2019) or discuss the hedging ability of (non)dependent assets in times of financial turmoil (e.g., Arif et al., 2021). However, since the Diebold and Yilmaz framework only provides an estimate of the average connectedness when an average shock hits the network (Pham and Cepni, 2022), extensions in terms of the Quantile VAR are employed, as for instance, climate risk at upper (lower) quantile might influence stock and bond markets differently than at the median quantile. This approach, introduced by Ando et al. (2022) and extended by Chatziantoniou et al. (2022), captures both positive shocks at higher quantiles and negative shocks at lower quantiles to assess whether connectedness depends on the magnitude of the shock. This is particularly relevant, as financial markets may react differently to small versus extreme climate risk shocks, leading to nonlinear spillover effects. To calculate the connectedness metrics, a quantile vector autoregression (QVAR) of order p is utilized as of:

$$y_t = \mu(\tau) + \sum_{j=1}^p \Phi_j(\tau) y_{t-j} + u_t(\tau), \quad u_t(\tau) \sim \mathcal{N}(0, \Sigma(\tau)) \quad (4.1)$$

where y stores the log returns of stock and bond indices and the unexpected change in textual climate risk. U_t is vector of shocks that are allowed to be contemporaneously correlated with a variance-covariance matrix Σ . Applying Wold's theorem, one gets an MA-representation of the QVAR(p) as of:

$$y_t = \mu(\tau) + \sum_{h=0}^{\infty} A_h(\tau) u_{t-h} \quad (4.2)$$

where each variable now depends on own past shocks and variable j 's past shocks recursively derived from the VAR coefficient matrix at different quantiles.

³⁹On the contrary, traditional variance decomposition, Choleski decomposition, does not assume that shocks are contemporaneously correlated, but depend on the ordering of variables.(i.e., one variable affects another but not vice versa).

Next, the H-step-ahead forecast of y_t due to past shocks is calculated as:

$$\tilde{Y}_{t+H} = \sum_{h=0}^{H-1} A_h(\tau) u_{t+H-h} \quad (4.3)$$

with A being the MA coefficients that describe how past shocks propagate over time and u_{t+H-h} represents the shock innovations due to unexpected movements in the series. By comparing the forecast at horizon H with the actual value, a total forecast error can be derived as of:

$$\epsilon^{t+H} = Y^{t+H} - \tilde{Y}^{t+H} \quad (4.4)$$

To assess the uncertainty of these forecasts, the variance of the forecast error is computed:

$$Var(\epsilon_{i,t+H}) = \sum_{h=0}^{H-1} (e_i' A_h(\tau) \Sigma A_h'(\tau) e_i) \quad (4.5)$$

This equation represents the total forecast error variance of variable i at horizon H determined by the comovement of shocks (via the variance-covariance matrix Σ) and the transmission of past shocks over time (via the moving average coefficients A_h).

The total forecast error variance is decomposed by applying the Diebold and Yilmaz framework (2012), which utilizes Forecast Error Variance Decomposition (GFEVD), introduced by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) to measure how much of the forecast error variance of series i is explained by shocks to itself and by shocks from all other series j .

$$\theta_{ij}^g(H) = \frac{\sigma(\tau)_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h(\tau) \Sigma(\tau) e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h(\tau) \Sigma(\tau) A_h'(\tau) e_i)} \quad (4.6)$$

where $\theta_{ij}^g(H)$ represents the contribution of shocks in variable j to the forecast error variance of variable i at horizon H , σ_{jj} is the standard deviation of the innovation for variable j at quantile τ , A_h are the moving average matrices, Σ is the variance-covariance

matrix of residuals, and e_i and e_j are selection vectors that extract the i -th or j -th element.

The numerator of equation 4.6 shows how much shocks from variable j contribute to the forecast error variance of variable i at different quantiles, therefore establishing a spillover measure between variable j and i , while the denominator is the total forecast error variance for variable i (equation 4.5). Since the shocks are not orthogonalized, the variance decompositions do not necessarily sum to 1. To fix this, Diebold and Yilmaz (2012) normalize:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)} \quad (4.7)$$

ensuring that the total variance contributions sum to 1. Using the normalized forecast error variance decompositions different spillover measures can be derived: the total connectedness index, which captures the average overall spillover intensity by shocks from all other variables is defined as:

$$S^g(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \cdot 100 \quad (4.8)$$

Directional spillovers between market i and all other markets j are defined as follows:

$$TO = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}^g(H)}{N} \times 100. \quad (4.9)$$

$$FROM = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ij}^g(H)}{N} \times 100. \quad (4.10)$$

where TO measures the return volatility spillovers transmitted by asset i to all other assets j at a specific quantile, and FROM measures the spillovers received by i from all

other j 's at specific quantiles. A net spillover measure from equation 4.9 and 4.10 can be derived as:

$$NET_i = TO_i - FROM_i \quad (4.11)$$

If the net spillover is above 0 (below 0) series i is a net transmitter (receiver) of shocks to all other series j .

Finally, pairwise spillovers are defined as:

$$NPDC = \left(\frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} \right) \times 100. \quad (4.12)$$

While the QVAR examines if shocks propagate differently at different levels of the series distribution, it does not account for spillovers across different quantile levels of two variables (e.g., the effect of Climate Risk at the 90th quantile on SLBs at the 10th quantile and vice versa), limiting its ability to capture asymmetric relationships across quantiles.

To overcome this, the Quantile-on-Quantile Connectedness (QQC) measure of Gabauer and Stenfors (2024) is utilized. QQC extends the QVAR framework by handling bivariate interactions between quantiles of two different series, allowing for a richer characterization of asymmetric spillovers. This approach allows examining spillovers between different quantiles of series to detect directly and reversely related quantiles, which might reveal different spillover dynamics during extreme market conditions.⁴⁰ Unlike QVAR, where τ is a scalar (Equation 4.1-4.6), QQC generalizes this by treating τ as a vector, allowing simultaneous interactions between multiple quantiles of both variables. Thus, QQC provides a richer representation of asymmetric spillover dynamics.

⁴⁰For instance, during periods of high Climate Risk ($\tau_1 = 0.90$), investors may exit Sustainable-Linked Bonds (SLBs), causing SLBs to drop to lower quantiles ($\tau_2 = 0.10$). This suggests a negative connectedness between high Climate Risk and weak SLB performance.

4.4.2 DCC-GARCH

While the connectedness and spillover analysis capture the directional influence of shocks by measuring how much an asset's return variability movement is influenced by the innovations of another series, it does not necessarily indicate that assets comove consistently in response.⁴¹ Therefore, in the following it is examined if climate risk and (ESG) assets co-move in a consistent pattern over time and if (ESG) assets might hedge climate risk.

The DCC-GARCH model, introduced by Engle (2002), extends the traditional multivariate GARCH model by allowing for time-varying correlations between asset returns and can be specified in its general form as DCC-GARCH (1,1). Model parameters are estimated using the two-step quasi-maximum likelihood estimation (QMLE) procedure. In the first step, univariate GARCH models are fit to each series to obtain standardized residuals. In the second step, the dynamic correlations are estimated.

$$y_t = \mu_t + u_t, \quad (4.13)$$

y_t represents the vector of asset returns, μ_t is the conditional mean, and u_t is the error term, represented by a time-varying covariance matrix H_t and a vector of i.i.d errors ϵ_t :

$$u_t = H_t^{1/2} \epsilon_t \quad (4.14)$$

The conditional variance-covariance matrix H_t is symmetric and positive definite, incorporating the time-varying conditional variances (D_t) and the time-varying conditional correlation matrix (R_t):

$$H_t = D_t R_t D_t. \quad (4.15)$$

Each diagonal element of D_t , representing the conditional variance of an individual asset, is modeled using a univariate GARCH(1,1) process:

⁴¹For instance, a large net connectedness measure could indicate that Green Bond returns are highly impacted when Climate Risk experiences a shock, but it does not clarify whether Green Bond prices rise or fall as a result. The metric simply shows how much Climate Risk's innovations explain the variance of Green Bonds' forecast errors, rather than the sign of those returns.

$$h_{i,t} = \omega_i + \alpha_i u_{i,t-1}^2 + \beta_i h_{i,t-1}, \quad (4.16)$$

where $h_{i,t}$ is the conditional variance of asset i , ω_i is a constant, α_i captures the impact of past squared residuals, and β_i captures the persistence of past variance. The diagonal elements of D_t are obtained as:

$$D_t = \text{diag}(\sqrt{h_{1,t}}, \sqrt{h_{2,t}}, \dots, \sqrt{h_{N,t}}). \quad (4.17)$$

Next, a time-varying correlation matrix R_t can be defined with standardized residuals, modeled by a separate GARCH like process to ensure the positivity of R , a proxy process Q_t (Saeed et al., 2020) is proposed as follows:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha\epsilon_{t-1}\epsilon'_{t-1} + \beta Q_{t-1}, \quad (4.18)$$

where: Q_t is the dynamic correlation proxy matrix at time t , \bar{Q} is the unconditional correlation matrix of standardized residuals, ϵ_t are the standardized residuals from a GARCH process, α captures the effect of lagged shocks, and β captures the effect of past correlations. Since Q_t is not a proper correlation matrix, it must be standardized to obtain R_t :⁴²

$$R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2}. \quad (4.19)$$

Once both D_t and R_t are estimated, the full conditional covariance matrix H_t is reconstructed (equation 4.15). The dynamic conditional correlation coefficient between asset i and asset j at time t is given by:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}. \quad (4.20)$$

⁴²This transformation ensures that the diagonal elements of R_t are equal to 1 and the off-diagonal elements represent the time-varying conditional correlations between asset returns.

These time-varying correlation coefficients allow to assess whether (ESG) assets exhibit stronger co-movement with climate risk. Note that positive correlation might indicate diversification and hedging benefits against climate risk here.⁴³

4.4.3 Portfolio-Analysis

It remains to be examined whether ESG-related assets can hedge equity portfolios during periods of elevated climate risk. When risk surges, ESG-oriented investors may reallocate toward sustainable assets, potentially supporting their prices and making them attractive hedging instruments.

Therefore, the dynamic conditional correlations and conditional standard deviations retrieved from the DCC-GARCH model are used for portfolio analysis under climate risk. Specifically, the optimal bivariate portfolio weight approach of Kroner and Ng (1998) is applied to compute time-varying optimal portfolio weights in a bivariate portfolio. The weights are chosen to minimize the variance and are dynamically adjusted based on a changing risk environment.

The optimal allocation at time between two assets x and y is given by:

$$w_{x/y,t} = \frac{h_{y,t} - h_{x/y,t}}{h_{x,t} - 2h_{x/y,t} + h_{y,t}} \quad (4.21)$$

with the following weight constraints:

$$w_{x/y,t} = \begin{cases} 0, & \text{if } w_{x/y,t} < 0 \\ w_{x/y,t}, & \text{if } 0 \leq w_{x/y,t} \leq 1 \\ 1, & \text{if } w_{x/y,t} > 1 \end{cases} \quad (4.22)$$

This formula minimizes portfolio variance by balancing the variance of each asset and their conditional covariance. X represents a passively managed equity portfolio tracking the European stock market (Stoxx600), and y corresponds to an ESG-related asset. The optimal portfolio weight represents the proportion of a one-dollar portfolio allocated to the Stoxx600 index, with the remainder invested in the ESG asset. Intuitively, if asset y

⁴³This stands in contrast to traditional asset diversification, where negative correlation is desirable, but climate risk is modeled as a risk indicator here, rather than a financial asset.

has a lower variance and weak correlation with the Stoxx600, a larger weight will shift toward it—reducing overall portfolio volatility.

To evaluate the potential hedging benefits of ESG assets, a climate risk threshold is set at the 90th percentile, following Cepni et al. (2022), implying that the hedging strategy is only activated when climate risk exceeds this threshold. In such periods, the unhedged equity portfolio is supplemented with ESG-related assets based on the optimal portfolio weights.

In contrast to in-sample approaches, where the entire dataset is used to recalibrate optimal portfolio weights simultaneously (and the hedge is applied on the same day the threshold is exceeded), I rely on a rolling window approach to estimate out-of-sample one-step-ahead conditional correlations.⁴⁴ In this framework, DCC-GARCH model parameters are estimated using the most recent 100 observations, and one-step-ahead forecasts for variances, covariances, and optimal portfolio weights are calculated. Consequently, if climate risk exceeds the threshold on day t , the portfolio is rebalanced on day $t+1$ based solely on information available by the end of day t , thus avoiding look-ahead bias.

Finally, to assess the overall performance between the hedged and unhedged portfolio, two portfolio metrics are used: the Sharpe-Ratio and the Hedging-Effectiveness.

First, the return of the hedged portfolio is computed as:

$$r_w = w_{ijt}r_{it} + (1 - w_{ijt})r_{jt} \quad (4.23)$$

The Sharpe-Ratio can be written as:

$$SR = \frac{\bar{R}_p}{\sigma_p} \quad (4.24)$$

with the average portfolio return in the numerator and the portfolio's standard deviation in the denominator.

Finally, the Hedging-Effectiveness is defined as:

⁴⁴on the contrary to in-sample hedging, where full data is used to recalibrate optimal portfolio weights simultaneously if climate risk exceeds a critical value, it is more realistic in practice to set the hedge at $t+1$ based on the information by the end of day t .

$$HE = \frac{\text{Variance unhedged} - \text{Variance hedged}}{\text{Variance unhedged}} \quad (4.25)$$

A higher HE value indicates better hedging effectiveness, implying a greater reduction in portfolio risk due to the ESG hedge.

This framework allows for a realistic assessment of how ESG assets perform as climate risk hedges, using dynamic allocation strategies and robust performance metrics. The next section presents the empirical results.

4.5 Empirical Results

Next, the results of the empirical approach are presented.

4.5.1 Evidence on connectedness

Tables 4.2 and 4.3 present the return connectedness measures derived from the classical Diebold and Yilmaz framework (2012, 2014). These measures examine how average shocks to climate risk—measured in terms of transition risk (Table 4.2) and physical risk (Table 4.3)—as well as shocks to conventional and ESG-related bonds, stocks, and gold, contribute to the return variability of each individual asset.

Tables 4.2 and 4.3: Connectedness Tables

	ClimateRisk	Stoxx600	StoxxSus	Wilderhill	EURGB	EURSLB	Gold	EURCB	FROM
ClimateRisk	84.93	2.62	2.60	1.04	2.36	2.30	1.89	2.26	15.07
Stoxx600	0.75	36.68	35.98	9.03	4.28	5.01	3.31	4.97	63.32
StoxxSus	0.77	35.88	36.52	8.70	4.39	5.18	3.29	5.27	63.48
Wilderhill	1.43	11.96	11.56	61.31	3.11	3.88	2.73	4.03	38.69
EURGB	0.73	3.41	3.58	1.62	30.66	28.08	3.82	28.10	69.34
EURSLB	0.69	3.90	4.15	1.92	26.88	29.58	3.92	28.96	70.42
Gold	1.07	5.41	5.43	2.88	7.36	7.99	62.27	7.60	37.73
EURCB	0.68	3.90	4.26	2.02	26.86	28.93	3.79	29.57	70.43
TO	6.12	67.08	67.55	27.21	75.24	81.36	22.75	81.18	428.49
NET	-8.96	3.75	4.07	-11.48	5.90	10.95	-14.98	10.75	61.21/53.56

Table 4.2: Connectedness Table with transition climate risk

	ClimateRisk	Stoxx600	StoxxSus	Wilderhill	EURGB	EURSLB	Gold	EURCB	FROM
ClimateRisk	86.68	2.46	2.31	1.78	1.59	1.68	1.70	1.80	13.32
Stoxx600	1.30	36.53	35.82	9.09	4.20	4.88	3.34	4.83	63.47
StoxxSus	1.31	35.74	36.39	8.79	4.30	5.04	3.31	5.12	63.61
Wilderhill	0.64	12.13	11.75	61.54	3.19	3.92	2.75	4.08	38.46
EURGB	0.68	3.34	3.50	1.65	30.70	28.12	3.87	28.13	69.30
EURSLB	0.71	3.82	4.05	1.93	26.91	29.62	3.96	29.00	70.38
Gold	1.04	5.39	5.40	2.90	7.43	8.02	62.19	7.63	37.81
EURCB	0.69	3.82	4.15	2.03	26.89	28.97	3.83	29.61	70.39
TO	6.37	66.70	66.99	28.17	74.52	80.64	22.78	80.60	426.75
NET	-6.95	3.22	3.38	-10.29	5.21	10.26	-15.04	10.21	60.96/53.34

Table 4.3: Connectedness Table with physical climate risk

Tables 4.2 and 4.3 report connectedness measures based on a static QVAR model with a lag length of order 1 and a 20-step ahead generalized forecast error variance decomposition. The From column accumulates the spillovers a series receives, while the TO row accumulates the spillovers a series transmits to all other series. The Net connectedness subtracts the TO and the From values.

The rows in the table display the spillovers received by series i from other markets j , while each column shows what series i contributes to the forecast error variance of series j .

The penultimate row reports the net return connectedness, defined as the aggregated difference between shocks transmitted to all other series and those received from them (see Equation 4.11). A net value above 0 indicates that an asset is a net transmitter of shocks, whereas a net value below 0 indicates that it is a net receiver.

Diagonal elements in both tables show how much of asset i 's return variability is driven by own shocks (for instance, Table 4.2 (4.3) shows that 36.68% (36.53%) of the Stoxx 600 return forecast error variance is explained by own shocks. Transition risk (84.93%), physical risk (86.68%) and gold (around 62%) are largely driven by their own dynamics rather than external shocks, reflecting a high degree of idiosyncratic behavior. As expected, some series—such as green and conventional bonds—are strongly interconnected, consistent with previous findings in the literature (e.g., Reboredo, 2018).

Of particular interest are the shock spillovers between both types of climate risk and the other assets. Transition Climate Risk is a net shock transmitter to the Wilderhill Clean Energy index, and a net receiver from all other series mostly pronounced in equity markets, particularly the Stoxx 600 and the Stoxx Sustainability. Physical risk is a shock receiver from all other series, but mostly from the two equity indices Stoxx 600 and Stoxx 600 Sustainability. On average, transition risk exhibits a lower net connectedness value (-8.96) than physical risk (-6.95), confirming its stronger role as a shock receiver on average.

While Tables 4.2 and 4.3 show average spillovers over the entire sample, Appendix Figures C.1.3 and C.1.4 provide a time-varying perspective of net connectedness between the individual series i and all other series j , which helps assess regime shifts or structural changes. A net value above 0 (below) indicates that the series is a net transmitter (receiver) of shocks. The upper left plots show that transition climate risk is a net receiver of shocks in the system mostly, except for the middle of 2023 and the middle of 2024 where it becomes a shock transmitter. Additionally, clean energy and gold are shock receivers in both systems, while both the stock and the bond market transmit shocks.⁴⁵ Compared to transition risk, the upper left climate risk net connectedness plot of Appendix figure C.1.4 indicates, that physical risk more often transmits shocks to the system: especially by the end of 2022, the middle of 2023 and the middle of 2024.

4.5.2 Evidence on connectedness with QVAR

The QVAR framework allows us to assess how spillovers vary across the distribution of climate risk and asset returns, capturing the effects of extreme shocks—both positive (upper quantiles) and negative (lower quantiles). This helps identify whether return

⁴⁵In 2022, stocks are also shock receivers, most likely based on the changing interest rate environment.

connectedness intensifies during market stress and whether the direction of spillovers depends on the nature of the shock.

Figures 4.1 and 4.2 plot the results of the quantile connectedness approach based on equations 4.1 to 4.6 by examining how shocks propagate through the system at different quantiles.

The y-axis denotes the quantile level of climate risk, ranging from 0.1 (lower tail) to 0.9 (upper tail). Positive values (red) represent periods when climate risk acts as a net shock transmitter across all other series; negative values (blue) indicate net shock reception.

Figure 4.1: Net total directional connectedness transition climate risk

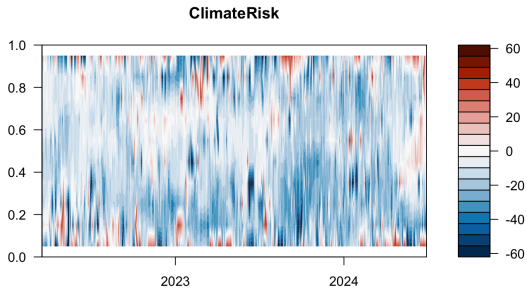


Figure 4.1: Net total directional connectedness for transition climate risk, estimated using a 100-day rolling window QVAR model (lag = 1, forecast horizon = 20).

Figure 4.2: Net total directional connectedness physical climate risk

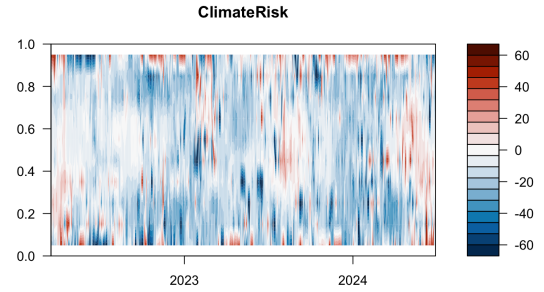


Figure 4.2: Net total directional connectedness for physical climate risk, estimated using a 100-day rolling window QVAR model (lag = 1, forecast horizon = 20).

For instance, when climate risk is at the median, both transition and physical climate risks function as net receivers of shocks across the system. For transition risk, only at the sample end (May and June 2024) the spillover to other assets is positive, while the physical risks plot exhibits shades of red by mid-2023 and mid-2024 where shocks spill over from climate risk to other assets, consistent with the net-connectedness plots of the classical Diebold and Yilmaz framework (2012, 2014).

At the tails of the distribution—particularly at the 10th and 90th quantiles—climate risk more frequently transmits shocks to other assets. This is especially pronounced for transition climate risk in mid-2023 and the first quarter of 2024, and for physical risk in the first half of 2022, autumn 2023, and mid-2024.

These findings indicate that climate-related shocks propagate more strongly under extreme conditions, highlighting the importance of accounting for nonlinear dynamics in risk modeling. Further, they support Hypothesis 1, suggesting that climate risk—especially under extreme regimes—acts as a transmitter of return volatility, indicating partial but

not complete pricing in markets.

4.5.3 Evidence on connectedness with QQC

Finally, a QQC approach is employed. Unlike the system-wide QVAR analysis, the QQC framework focuses on pairwise interactions between climate risk and individual asset returns. This approach compares how the τ_1 quantile of climate risk impacts the τ_2 quantile of the return of series j and vice versa.

The QQC measures depicted in figures 4.3 and 4.4 are based on a 100-day rolling window QVAR, lag length of order 1 and a 20-step ahead forecast horizon, as in Chatziantoniou et al. (2021) and Gabauer and Stenfors (2024).

Figure 4.3: Net QQC transition risk

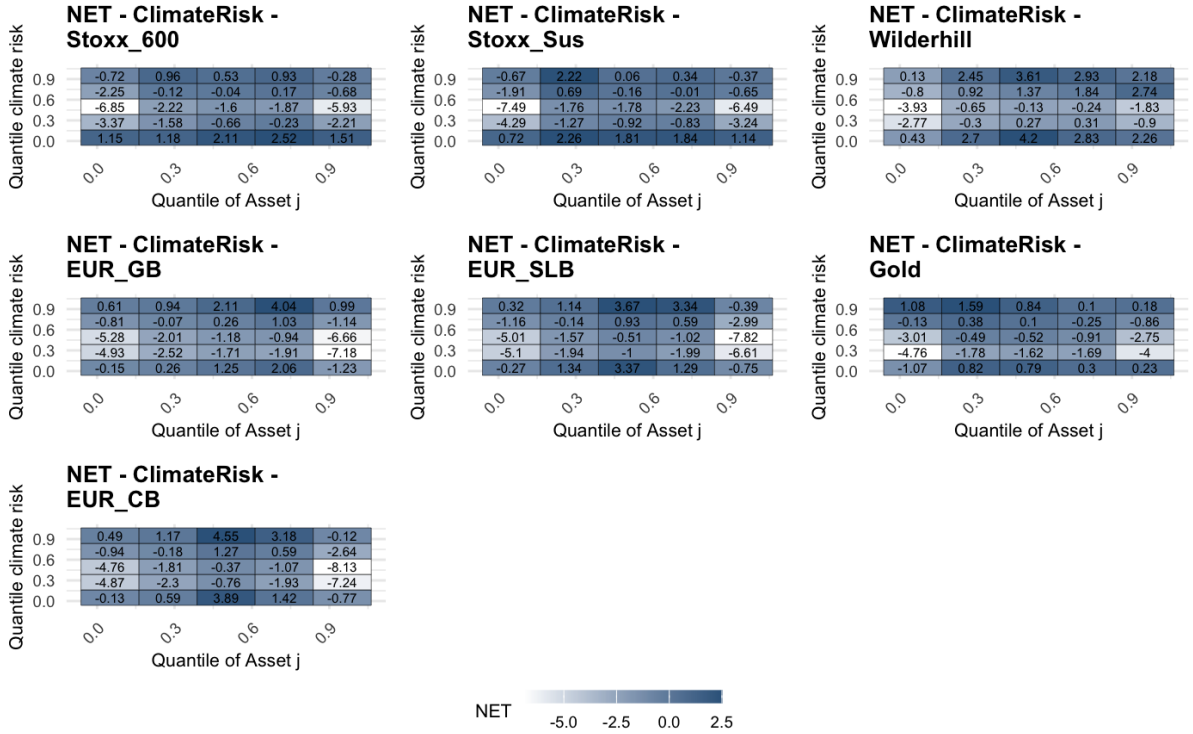


Figure 4.3: Net quantile-on-quantile connectedness between transition climate risk and all other series j . The results are based on a 100 day rolling VAR with lag length of order 1 and a 20 step-ahead generalized forecast error variance decomposition. The y axis stores the quantiles of the climate risk, while the x-axis stores the quantiles of each series.

Each panel in Figure 4.3 shows a 5x5 grid of quantile combinations between climate risk (vertical axis) and an asset return (horizontal axis).

The cell values represent the net directional connectedness from climate risk to asset j and a negative value (lighter shade towards white) would indicate that climate risk is a net receiver of shocks while a positive cell value means climate risk is a shock transmitter.

The seven panels of Figure 4.3 confirm the prior results:⁴⁶ Across the seven panels, most cells are negative, especially when climate risk is in the middle of its distribution. For instance, if both climate risk and Stoxx 600 are at the middle of their distributions, τ_1 , $\tau_2 = 0.5$, the net connectedness is -1.6.

At higher quantiles, climate risk tends to transmit shocks—particularly to bond markets when bond returns are at middle to upper quantiles. This is evident from the predominantly positive values in the upper rows of the EUR-GB, EUR-SLB, and EUR-CB panels. Vice versa, at reversed quantiles (i.e. lower climate risk and higher asset j quantile) this effect is also observable. Interestingly, when asset returns are at high quantiles, climate risk tends to absorb shocks from the system, as shown by the negative values in the last columns of each panel.

Next, Figure 4.4 presents the same analysis for physical risk. When both physical risk and series j are in the middle of the distributions, the evidence for net-connectedness is mixed. Similar to transition risk, high levels of physical risk tend to make it a shock transmitter. These effects are most pronounced for equity markets (Panels 1 and 2), while bond market responses (Panels 4, 5, and 7) are more heterogeneous. When physical risk is low and the asset is at a median quantile, the asset tends to receive shocks. Conversely, if the asset is at a high quantile, it transmits shocks to climate risk—reflected by the negative values in the last columns of each panel.

⁴⁶Note that the QQC accounts for bivariate connectedness now between climate risk and series j solely, the plots before accounted for a system of variables.

Figure 4.4: Net QQC physical risk

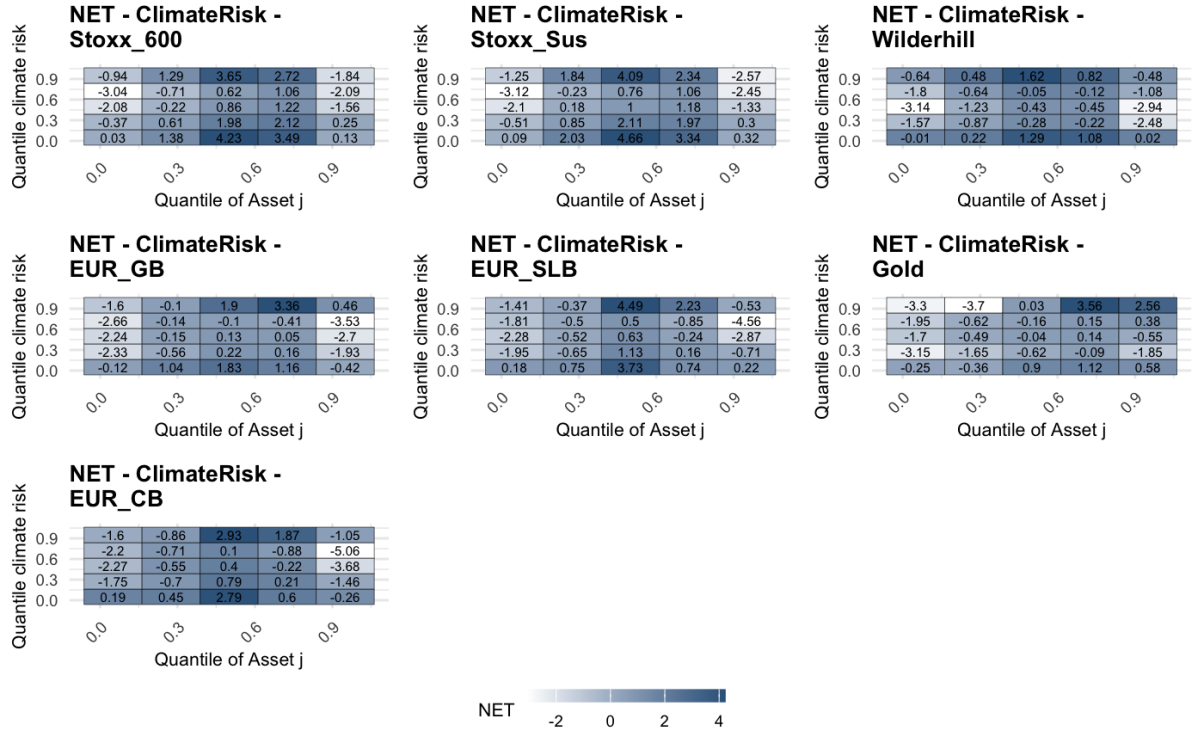


Figure 4.4: Net quantile-on-quantile connectedness between physical climate risk and all other series j . The results are based on a 100 day rolling VAR with lag length of order 1 and a 20 step-ahead generalized forecast error variance decomposition. The y axis stores the quantiles of the climate risk, while the x-axis stores the quantiles of each series.

Lastly, Appendix figures C.1.5 and C.1.6 plot the evolution of net connectedness between both physical and climate risk over time, by averaging across all bi-variate quantile combinations between climate risk and series j for day t smoothed over a 100-day window. Both figures reinforce the earlier findings: climate risk most often behaves as a net shock receiver, though it occasionally transmits shocks during stress periods—for instance by mid 2024.

4.5.4 Evidence on DCC-GARCH

This section presents the dynamic conditional correlations between climate risk (transition and physical) and various asset classes, including conventional and ESG-labeled bonds, equities, clean energy, and gold. Figures 4.5 and 4.6 plot these correlations over time, as derived from the DCC-GARCH model.

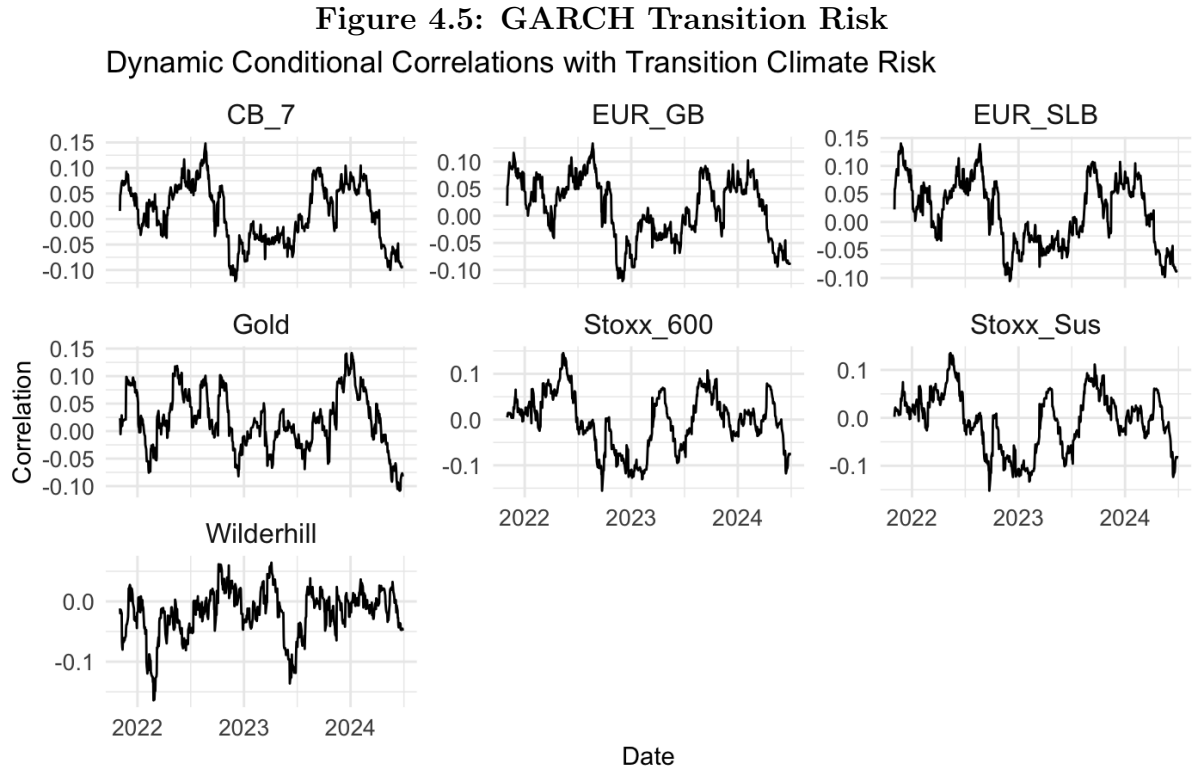


Figure 4.5: Dynamic conditional correlation between transition climate risk and series j

The three different bond markets - the European conventional bond market, green bonds and the SLBs - exhibit very similar patterns of correlation with transition risk. Initially, slightly positive in late 2021, correlations turned negative in early 2022 before peaking around mid-2022 (approximately 0.15). After dipping again, a resurgence in positive correlation is observed in the latter half of 2023 and early 2024. Gold exhibits spikes in correlation similar to those of the bond markets, peaking at the end of 2023. Interestingly, the stock market's (Stoxx600 and Stoxx-Sustainability) correlation with transition risk has patterns comparable to the bond while the clean energy Wilderhill index fluctuates around zero.

Among bonds, the SLB's correlation with transition climate risk is the highest, as Appendix Table C.2.1 shows (0.016). This is broadly consistent with the findings of Jin et al. (2020) that carbon risk is positively related to green bonds and with Cepni et al. (2022) who show that the time varying-conditional correlation between transition risk and green bonds are positive. Also, gold exhibit a small positive correlation on average (0.018), while conventional, clean energy and sustainable equities are slightly negatively related to climate risk. Consequently, bonds and gold might serve as reliable instrument for the implementation of hedging strategies (i.e., as climate risk spikes, the bonds gain); however, conditional correlation on average is pretty small above zero, which complicates the design of risk management strategies. Due to the limited strength of these correla-

tions, hedging strategies would likely be effective only during periods of elevated climate risk—for instance, when the climate risk index crosses its 90th percentile.

In contrast, Figure 4.6 shows the dynamic conditional correlations with physical climate risk.

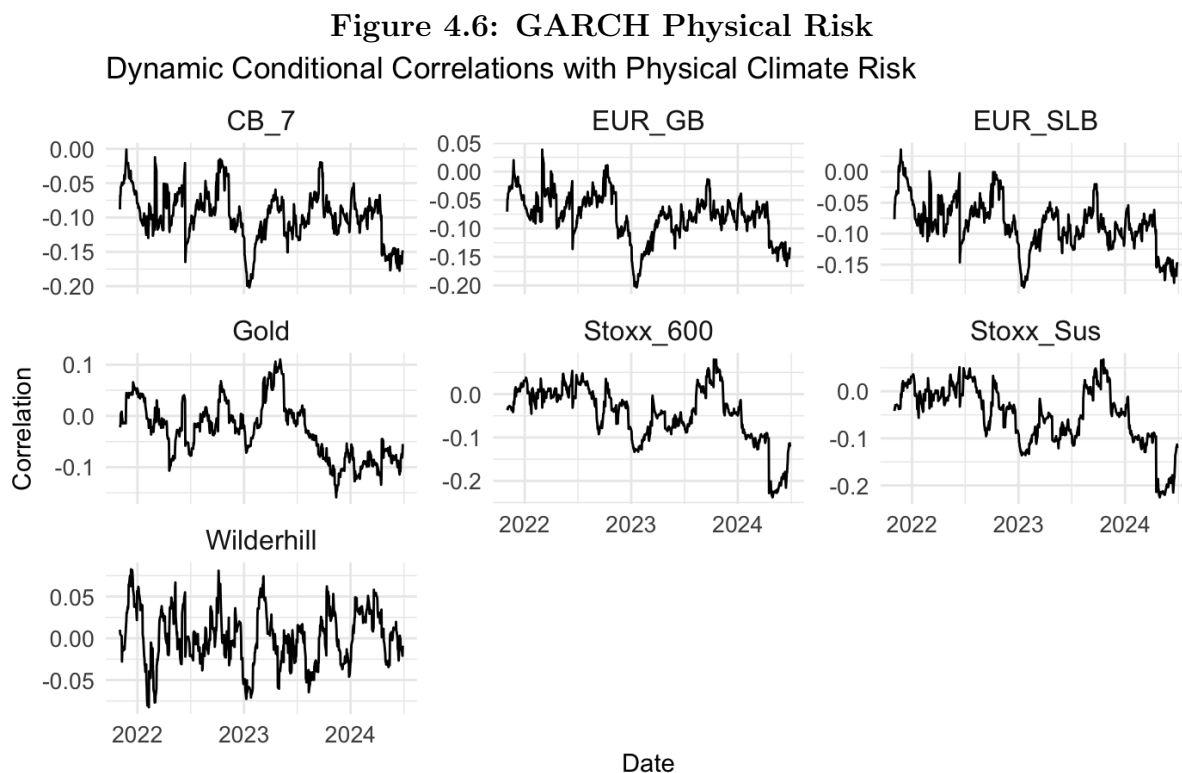


Figure 4.6: Dynamic conditional correlation between physical climate risk and each series.

Across most assets—especially bonds—correlations remain predominantly negative throughout the sample. Conventional bonds exhibit the strongest average negative correlation (-0.097) as Appendix Table C.2.2 summarizes, followed by gold and equity indices, with the end of 2023 being an exception for stocks. These results imply that most ESG assets do not co-move positively with physical climate risk, and thus may not serve as strong hedging tools in the face of physical climate threats.

4.5.5 Evidence on Portfolio-Analysis

Building on the findings from the DCC-GARCH analysis — where sustainable bond assets and gold showed positive (albeit modest) co-movement with transition climate risk — this section evaluates the hedging performance of these assets in a portfolio context. Following Cepni et al. (2022), an unhedged European equity portfolio (STOXX 600) is dynamically supplemented with individual green or alternative assets whenever climate risk exceeds its 90th percentile. Since spillovers were strongest in the tails, this threshold-based strategy

aims to test whether climate-related assets provide effective hedging during periods of heightened risk.

Daily Optimal Weights for portfolio allocation are calculated using time-varying conditional correlation and volatility from the DCC-GARCH model, as in equation 4.21. The re-balancing decision is made one day after the climate risk signal exceeds the threshold, ensuring all allocations are based on information available at time t and avoiding look-ahead bias. During periods of lower climate risk, the investor remains unhedged and holds its equity portfolio. The hedged and unhedged strategies are evaluated using average return, standard deviations, Sharpe-Ratio, and Hedging Effectiveness.

The following table 4.4 stresses the performance for transition risk.

Table 4.4: Performance Metrics of Transition Hedging Strategies

Strategy	Mean_Return	StdDev	Sharpe_Ratio	Hedging_Effectiveness
Unhedged_Stoxx	0.0198	0.8232	0.0240	
Hedged_Weight_Stoxx_Sus	0.0206	0.8219	0.0251	0.0031
Hedged_Weight_Wilderhill	0.0199	0.8251	0.0241	-0.0045
Hedged_Weight_EUR_GB	0.0273	0.8001	0.0341	0.0554
Hedged_Weight_EUR_SLB	0.0280	0.8026	0.0349	0.0494
Hedged_Weight_Gold	0.0213	0.8077	0.0263	0.0372
Hedged_Weight_CB	0.0256	0.8053	0.0317	0.0429

Table 4.4 presents performance metrics for an unhedged Stoxx 600 equity portfolio and a set of hedged portfolios. When transition climate risk exceeds the 90th percentile threshold, a single asset is added to the portfolio at a time. Optimal allocation follows the methodology of Kroner and Ng (1998), using a 100-day rolling window to train the data. Hedging is implemented based on one-step-ahead forecasts.

The results provide several insights. First, hedging transition risk rewards the investor with higher average return, lower risk and consequently higher risk-adjusted returns (as the Sharpe-Ratio for the hedged portfolio is higher than for the unhedged portfolio), except for the Wilderhill Clean Energy index.

Second, and consistent with Cepni et al. (2022) and Yousaf et al. (2022), (ESG) bonds are most successful in hedging climate risk, amplifying prior findings of positive conditional correlation with transition risk and the higher net-connectedness at tail climate risk.

While the hedged green bond portfolio has the highest Hedging-Effectiveness of 5.54 percent, the SLB-portfolio’s risk-adjusted return (Sharpe-Ratio) is superior. Additionally, conventional bonds (CB-7) have superior portfolio metrics compared to sustainable equity indices and the Wilderhill clean energy index.⁴⁷

In contrast to transition risk, hedging physical climate risk proves more challenging.

Table 4.5: Performance Metrics of Physical Hedging Strategies

Strategy	Mean_Return	StdDev	Sharpe_Ratio	Hedging_Effectiveness
Unhedged_Stoxx	0.0198	0.8232	0.0240	
Hedged_Weight_Stoxx_Sus	0.0187	0.8242	0.0227	-0.0024
Hedged_Weight_Wilderhill	0.0193	0.8227	0.0235	0.0012
Hedged_Weight_EUR_GB	0.0036	0.7973	0.0045	0.0619
Hedged_Weight_EUR_SLB	0.0048	0.7975	0.006	0.0616
Hedged_Weight_Gold	0.0086	0.8074	0.0107	0.0380
Hedged_Weight_CB	0.0060	0.7997	0.0075	0.0563

Table 4.5 presents performance metrics for an unhedged Stoxx 600 equity portfolio and a set of hedged portfolios. When physical climate risk exceeds the 90th percentile threshold, a single asset is added to the portfolio at a time. Optimal allocation follows the methodology of Kroner and Ng (1998), using a 100-day rolling window to train the data. Hedging is implemented based on one-step-ahead forecasts.

The unhedged Stoxx portfolio has a higher mean and lower risk than the portfolios supplemented with exposure to the Sustainability Stoxx index and the Wilderhill clean energy index. Although bonds are an effective tool in reducing the portfolio risk to 0.80 percent (from 0.825) which corresponds to a 6% reduction in return volatility of the unhedged portfolio, this is at the cost of return and results in inferior sharpe-ratios. Gold exhibits the highest average return among the hedging assets for physical risk, but its hedging effectiveness remains modest (3.8%), and its Sharpe Ratio remains well below the unhedged benchmark.

These results align with the earlier DCC-GARCH findings and provide partial support for Hypothesis 2: ESG bonds—especially green and sustainability-linked bonds—can hedge

⁴⁷Note the three bond indices cannot be compared exactly here, because they couldn’t be matched on exact criteria. Since they differ (slightly) in terms of the average rating of bonds in the index and the modified durations (how the price of bonds in the index react to changing interest rates, one could not conclude that ESG bonds are superior than conventional bonds in hedging physical climate risk.

transition climate risk in equity portfolios. The positive conditional correlations translate into volatility reduction and improved Sharpe Ratios during high-risk periods. However, ESG bonds fail to hedge physical climate risk, offering little protection in response to acute environmental shocks.

The findings also support Hypothesis 3. Clean energy equities deliver minimal hedging benefits against either type of climate risk, consistent with their limited co-movement with climate risk and their equity-like exposure to market volatility.

4.6 Discussion

The findings reveal that climate risk transmits shocks to financial markets in an asymmetric way - depending on the type of climate risk and the asset class. ESG-labeled bonds, particularly green and SLBs, show potential for hedging transition risk, but are less effective in hedging physical risk.

While initial evidence from the Diebold and Yilmaz framework has shown that both transition and physical risk are net receivers of shocks and are affected by their own innovations mostly (85%) - stressing their independence in the system, evidence from the QVAR and QQC shows that both types of climate risk become net transmitters during tail events, indicating that investors react to climate risk shocks. Moreover, transition risk spills over primarily into bond markets, while physical risk affects equity markets more strongly. QQC results also suggest potential feedback loops, where high-return states in financial assets (e.g., bonds or stocks) transmit shocks back to climate risk. This may reflect changing investor sentiment or repricing of climate-sensitive exposure.

However, connectedness measures do not imply any hedging potential yet, as net connectedness measures how strongly shocks from series j increase the variability in i 's return, but not the direction of returns. Thus, while climate risk can impact ESG assets, it's not clear from these results whether ESG assets reliably co-move positively or negatively with risk. For that, co-movement patterns—captured by the DCC-GARCH model—are more informative. The DCC-GARCH results show that transition risk exhibits slightly positive and more stable correlations with ESG-related bond markets, particularly green bonds and SLBs which makes them a potential hedge. This interpretation is supported by portfolio analysis:

During periods of elevated transition risk, a portfolio dynamically hedged with ESG related bonds showed superior risk-adjusted returns compared to an unhedged equity portfolio. These results also align with the QQC findings, which show strong tail spillovers

from transition risk into bond markets, suggesting a pattern of investor flight into ESG bonds following transition-related shocks.

By contrast, correlations with physical risk are more volatile and often negative, particularly for bonds, though some short-lived positive relationships appear for gold and sustainable equities. Neither ESG assets nor (sustainable) stocks showed ability to hedge the Stoxx600 in times of high physical risk.

One likely explanation for this divergence is the nature of climate risk. Transition risk—linked to regulation, carbon pricing, and policy—is more systematically embedded in the structure of ESG bonds. Sustainability-linked-bonds, for instance, often have the predefined goal of achieving a carbon emission reduction until a predefined date (otherwise a penalty for non-achieving the target kicks in, mostly a coupon-step up for the bonds' residual maturity) making their design to be stronger aligned with transition pathways serving as a potential hedge in times of higher transition risk. Physical climate risk, however, typically stems from sudden, localized events (e.g., floods, wildfires, droughts) that are harder to forecast, less uniformly priced, and more difficult to hedge with existing ESG instruments.

These results are consistent with prior work. Although Yousaf et al. (2022) do not include climate risk measures into their study, they show that green bonds are the only sustainable asset with weak safe haven properties as they can hedge SP500 downturns and exhibit superior Sharpe-ratio and return volatility reduction than all other sustainable equities, clean energy or gold. They attribute this to the fixed-income nature of green bonds and their relatively stable cash flows. The hedging behavior observed here can also be interpreted through the lens of intertemporal hedging theory. Pastor, Stambaugh, and Taylor (2021) argue that green assets carry a hedge premium: investors are willing to pay more (and accept lower expected returns) for assets that perform better during periods of elevated risk. While this paper does not test for greenium directly, the findings suggest that investors indeed reallocate into ESG bonds during climate stress, reflecting their perceived protective value.

Taken together, the results underscore that hedging climate risk requires tailored strategies that account for the underlying risk type. While green and sustainability-linked bonds provide meaningful protection against transition risk, they are far less effective for physical risk.

In addition, the asymmetric and state-dependent responses indicate that markets do not fully price in climate risk, but rather react to shocks as they materialize, consistent with the first hypothesis. This has important implications for portfolio construction and cli-

mate risk management, especially as financial markets increasingly price in environmental risks in differentiated ways.

4.7 Conclusion

This study investigates how climate risk—distinguishing between transition and physical risk—affects the return dynamics and connectedness of ESG-labeled and conventional financial assets. Using quantile-based spillover frameworks (QVAR and QQC), DCC-GARCH models, and a portfolio optimization approach, the results show that climate risk shocks propagate asymmetrically across asset classes and risk types.

The findings provide partial empirical support for the hypotheses. Transition climate risk transmits shocks more prominently to ESG bond markets—especially during tail events—and these assets, in turn, offer moderate hedging effectiveness within equity portfolios. In contrast, physical climate risk has a weaker and more volatile transmission pattern and proves harder to hedge. Clean energy and sustainable equities fail to provide meaningful protection against either form of risk.

The results also carry important implications for investors, asset manager and policy-makers: First, bonds might be able to hedge an equity portfolio against transition risk. Especially sustainability-linked bonds and green bonds exhibited the most robust portfolio metrics and managers adjusting their portfolio exposures dynamically on transition risk with such bonds may benefit. Second, none of the assets used in this study could hedge physical risks, underscoring the need for more sophisticated financial assets. Finally, this paper offers different avenues for future research: first, due to data limitations, the sample size is short and could be extended. Sustainability-linked bonds are still a relatively new instrument, so it would be interesting to observe whether their hedging effectiveness persists. Additionally, the drivers of hedging effectiveness could be explored further. Lastly, the analysis could be extended to other markets.

Appendix C

C.1 Figures

Figure C.1.1 — Unexpected Climate Risk over Time

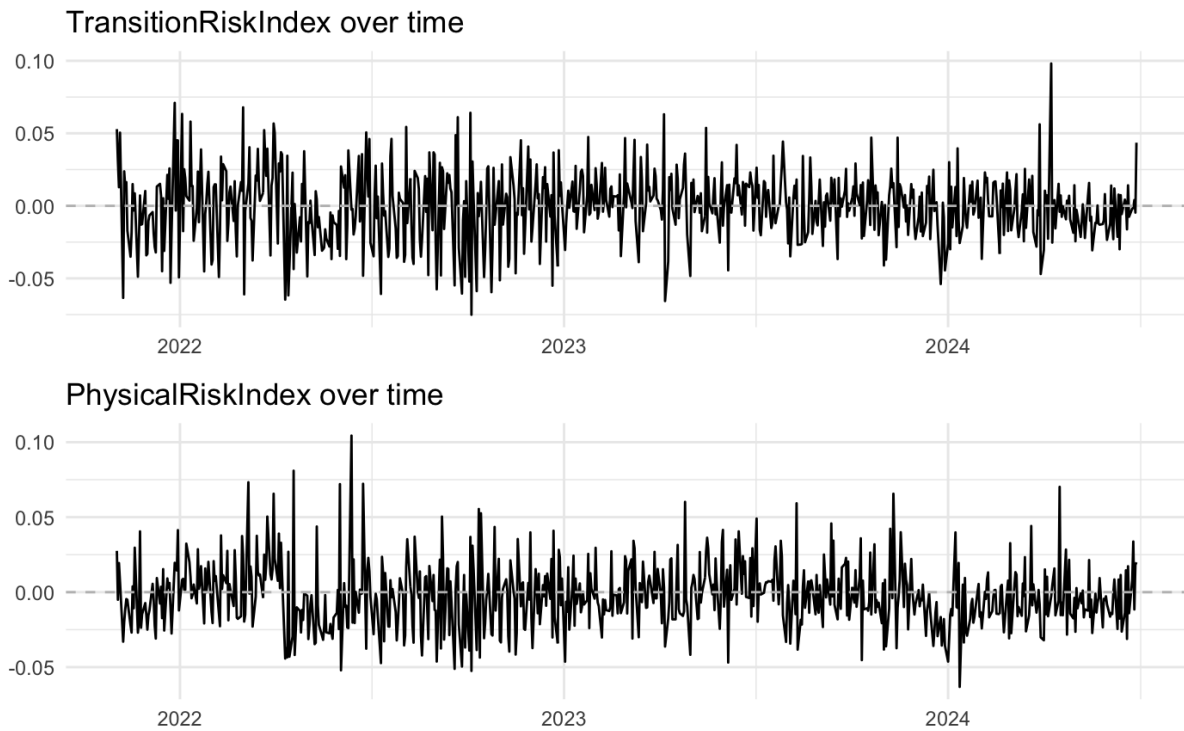


Figure C.1.1: Unexpected Climate Risk over time

Figure C.1.1 Description: Figure C.1.1 plots the Transition Risk Index and the Physical Risk Index over time between November 2021 and June 2024. The risk indices stem from residuals of an AR(1) process to extract unexpected changes in physical and transition risk.

Figure C.1.2 — Log Return of each series

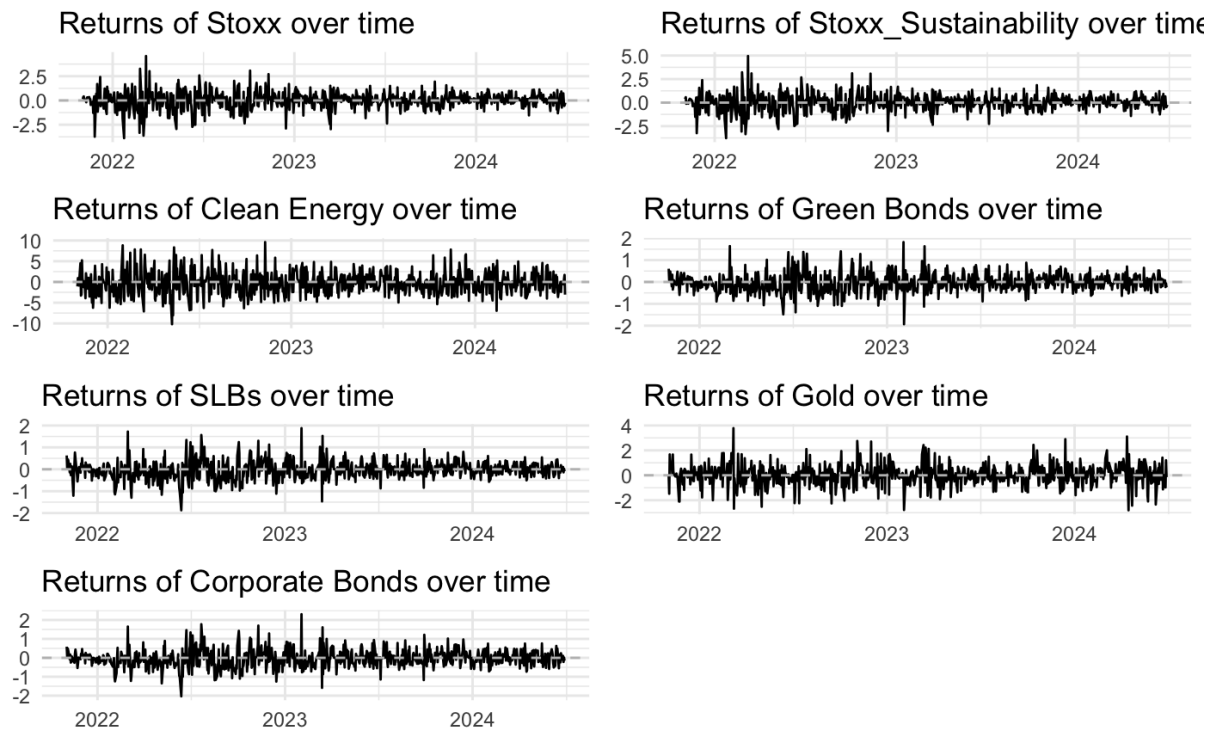


Figure C.1.2: Return of series

Figure C.1.2 Description: Figure C.1.2 plots the series' log-returns between November 2021 and June 2024 for the Stoxx 600, the Stoxx 600 Sustainability, the Wilderhill Clean Energy Index, the IBoxx Green Bond Index, the IBoxx Sustainability-Linked Bond Index, Gold, and the IBoxx Corporate Bond Index.

Figure C.1.3 and C.1.4 — Net Connectedness

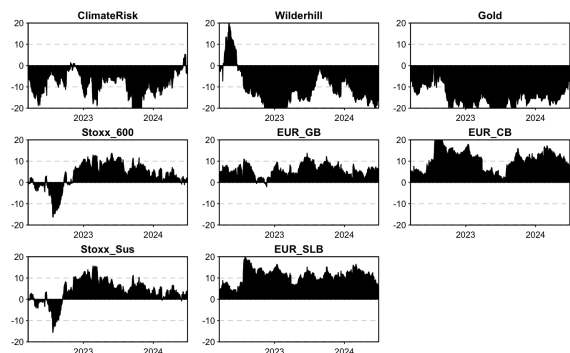


Figure C.1.3: Net Total Directional Connectedness — Transition Climate Risk

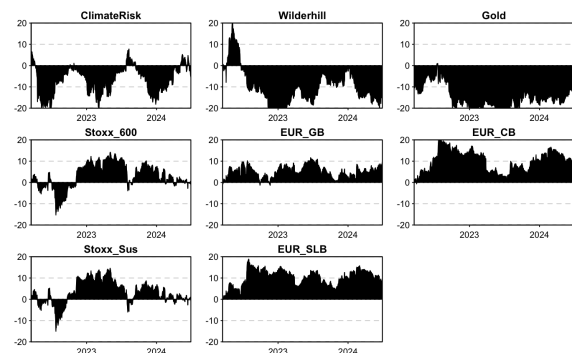


Figure C.1.4: Net Total Directional Connectedness — Physical Climate Risk

Note: Figures C.1.3 and C.1.4 plot the net total directional connectedness based on the Diebold and Yilmaz generalized forecast error variance decomposition. The y -axis displays the net connectedness, while the x -axis represents time. Values above zero indicate that a series transmits more shocks to all other series than it receives.

Figure C.1.5 and C.1.6 — Dynamical QQC-plots for transition risk (C.1.5) and physical risk (C.1.6)

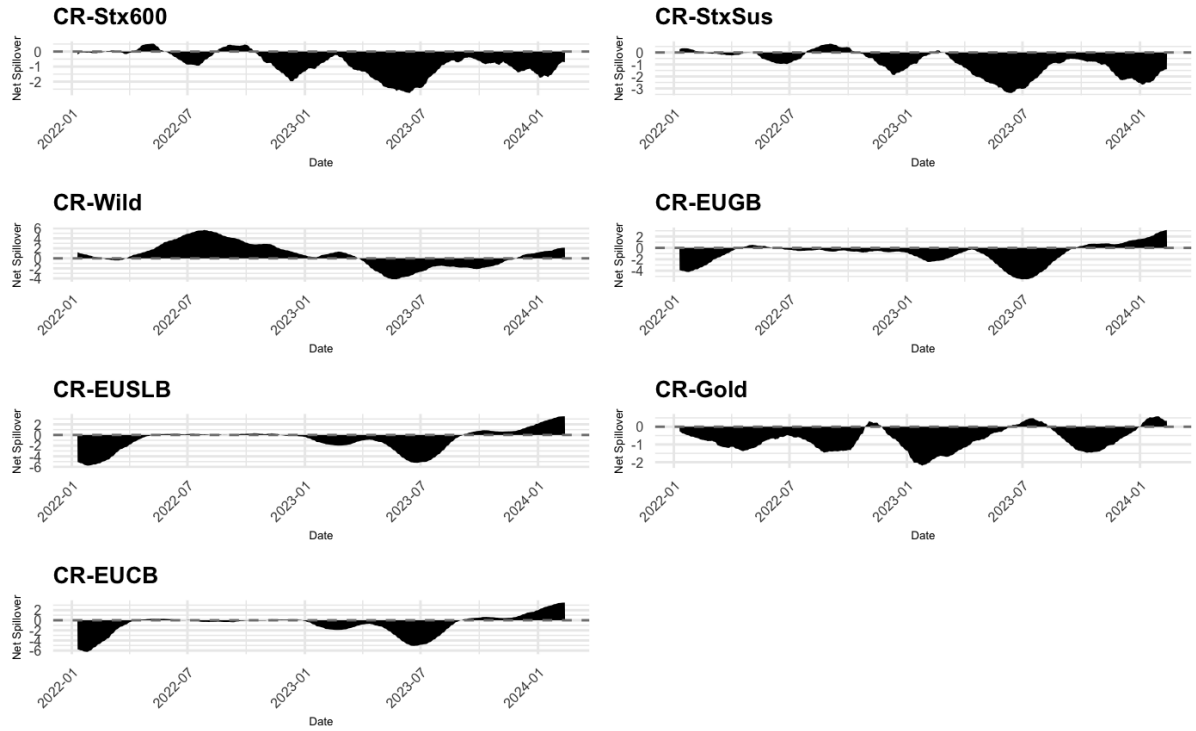


Figure C.1.5: Dynamic Transition QQC plot at different quantile-on-quantile combinations between transition risk and univariate series j .

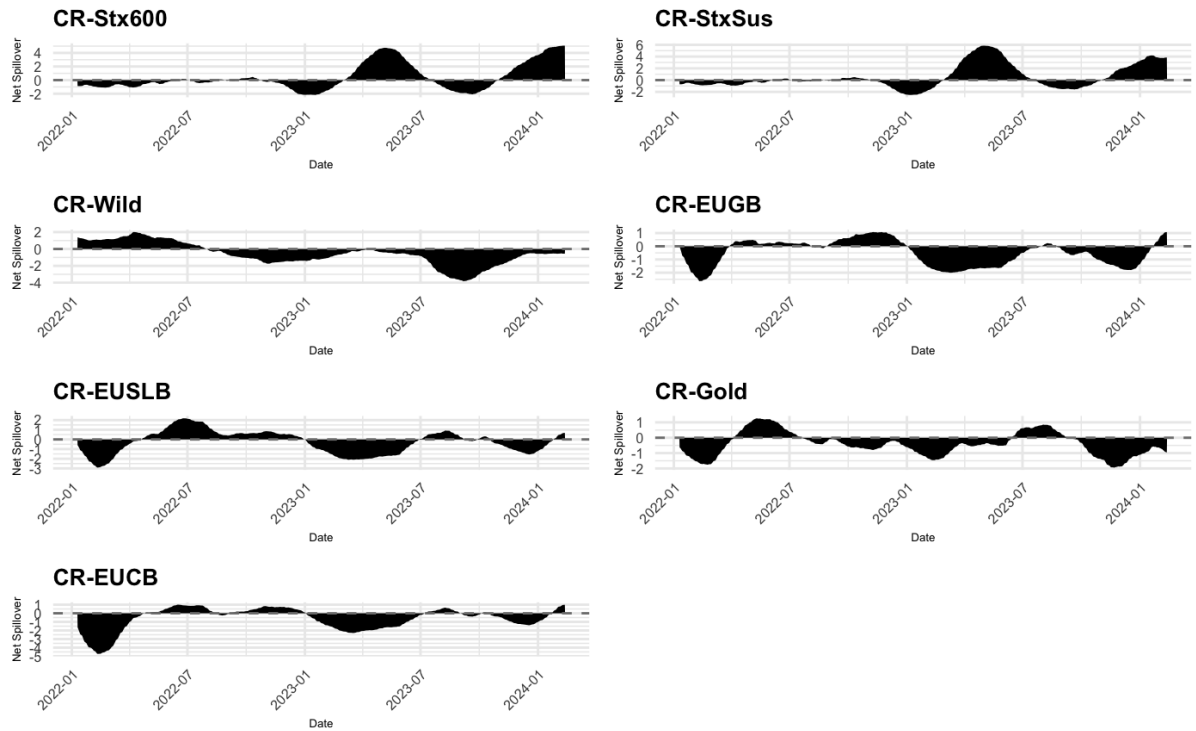


Figure C.1.6: Dynamic Physical QQC plot different quantile-on-quantile combinations between transition risk and univariate series j .

C.2 Tables

Table C.2.1: Summary Statistics of Dynamic Conditional Correlation vs. Transition Climate Risk

Statistic	Min	Mean	St. Dev.	Median	Max
Stoxx_600	−0.156	−0.003	0.062	0.002	0.145
Stoxx_Sus	−0.152	−0.005	0.061	0.001	0.135
Wilderhill	−0.164	−0.019	0.040	−0.012	0.064
EUR_GB	−0.120	0.014	0.057	0.019	0.134
EUR_SLB	−0.106	0.017	0.059	0.022	0.140
Gold	−0.108	0.019	0.052	0.015	0.142
CB_7	−0.122	0.011	0.058	0.011	0.148

Table C.2.2: Summary Statistics of Dynamic Conditional Correlation vs. Physical Climate Risk

Statistic	Min	Mean	St. Dev.	Median	Max
Stoxx_600	−0.238	−0.044	0.066	−0.035	0.080
Stoxx_Sus	−0.225	−0.050	0.064	−0.038	0.068
Wilderhill	−0.083	0.002	0.033	0.002	0.082
EUR_GB	−0.204	−0.078	0.041	−0.075	0.039
EUR_SLB	−0.187	−0.084	0.040	−0.085	0.036
Gold	−0.159	−0.029	0.056	−0.026	0.110
CB_7	−0.202	−0.097	0.037	−0.096	−0.001

References

- [1] Andersen, P. M. (2018), Yield curve modeling and a conceptual framework for estimating yield curves: Evidence from the European Central Bank's yield curves, *ECB Working Paper No. 27*.
- [2] Ando, T., Greenwood-Nimmo, M. and Shin, Y. (2022), Quantile Connectedness: Modeling Tail Behavior in the Topology of Financial Networks, *Management Science*, Vol. 68, No. 4, 2401-2431.
- [3] Ardia, D., Bluteau, K., Boudt, K. and Inghelbrecht, K. (2023), Climate Change Concerns and the Performance of Green vs. Brown Stocks, *Management Science*, Vol. 69, No. 12, 7607-7632.
- [4] Arif, M., Hasan, M., Alawi, S. M. and Naeem, M. A. (2021), COVID-19 and time-frequency connectedness between green and conventional financial markets, *Global Finance Journal*, Vol. 49, 100650.
- [5] Asquith, P. and Mullins, D. W. (1986), Equity Issues and Offerings Dilution, *Journal of Financial Economics*, Vol. 15, No. 1, 61-89.
- [6] Atz, U., Liu, Z., Bruno, C. and Van Holdt, T. (2023), Does sustainability generate better financial performance? review, meta-analysis, and propositions, *Journal of Sustainable Finance and Investment*, Vol. 13, No. 1, 802-825.
- [7] Bachelet, M. J., Bechetti, L. and Manfredonia, S. (2019), The green bonds premium puzzle: The role of issuer characteristics and third-party verification, *Sustainability*, Vol. 11, No. 4, 1098-1120.
- [8] Baker, M., Bergstrasser, D., Serafeim, G. and Wurgler, J. (2018), Financing the Response to Climate Change: The Pricing and Ownership of U.S. Green Bonds, *NBER Working Paper Series*, No. 25194.
- [9] Barber, B. M. and Loeffler, D. (1993), The "Dartboard" Column: Second-Hand Information and Price Pressure, *Journal of Financial and Quantitative Analysis*, Vol. 28, No. 2, 273-284.
- [10] Bats, J. V., Bua, G. and Kapp, D. (2024), Physical and transition risk premiums in euro area corporate bond markets, *ECB Working Paper*, No. 2899.
- [11] Bauer, R. and Hamm, D. (2014), Corporate Environmental Management and Credit Risk, *Working Paper*.

- [12] Baulkaran, V. (2019), Stock market reaction to green bond issuance, *Journal of Asset Management*, Vol. 20, 331-340.
- [13] Berman, S. L., Wicks, A. C., Kotha, S. and Jones, T. M. (1999), Does Stakeholder Orientation Matter? The Relationship between Stakeholder Management Models and Firm Financial Performance, *The Academy of Management Journal*, Vol. 42, No. 5, 488-506.
- [14] Berrada, T., Engelhardt, L., Gibson, R. and Krueger, P. (2022), The Economics of Sustainability-Linked Bonds, *Swiss Finance Institute Research Paper Series*, No. 820/2022.
- [15] Boehmer, E., Masumeci, J. and Poulsen, A. B. (1991), Event-study methodology under conditions of event-induced variance, *Journal of Financial Economics*, Vol. 30, 253-272.
- [16] Bolton, P. and Kacperczyk, M. (2021), Do investors care about carbon risk, *Journal of Financial Economics*, Vol. 142, No. 2, 517-549.
- [17] Bouri, E., Rognone, L., Sokhanvar, A. and Wang, Z. (2023), From climate risk to the returns and volatility of energy assets and green bonds: A predictability analysis under various conditions, *Technological Forecasting and Social Change*, Vol. 194, 122682.
- [18] Broeders, D., Jonge, M. and Rijsbergen, D. (2024), The European Carbon Bond Premium, *De Nederlandsche Bank*, Working Paper 798.
- [19] Brown, S. J. and Warner, J. B. (1980), Measuring Stock Price Performance, *Journal of Financial Economics*, Vol. 8, 205-258.
- [20] Brown, S. J. and Warner, J. B. (1985), Using Daily Stock Returns The Case of Event Studies, *Journal of Financial Economics*, Vol. 14, 3-31.
- [21] Bua, G., Kapp, D., Ramella, F. and Rognone, L. (2024), Transition versus physical climate risk pricing in European financial markets: a text-based approach, *The European Journal of Finance*, Vol. 30, No. 17, 2076-2110.
- [22] Deutsche Bundesbank (2019), The sustainable finance market: a stocktake, *Monthly Report*.
- [23] Capelle-Blancard, G. and Petit, A. (2019), Every Little Helps? ESG News and Stock Market Reaction, *Journal of Business Ethics*, Vol. 157, 543-565.
- [24] Cepni, O., Demirer, R. and Rognone, L. (2022), Hedging climate risks with green assets *Economics Letters*, Vol. 212, 110312.

- [25] Cepni, O., Demirer, R., Pham, L. and Rognone, L. (2023), Climate uncertainty and information transmissions across the conventional and ESG assets *Journal of International Financial Markets, Institutions and Money*, Vol. 83, 101730.
- [26] Chatziantoniou, I., Gabauer, D. and Stenfors, A. (2021), Interest rate swaps and the transmission mechanism of monetary policy: A quantile connectedness approach, *Economic Letters*, Vol. 204, 109891.
- [27] Chatziantoniou, I., Abakah, E. J. A., Gabauer, D. and Tiwari, A. K. (2022), Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets, *Journal of Cleaner Production*, Vol. 361, 132088.
- [28] Climate Bonds Initiative (CBI) (2017), Green Bond Highlights 2017.
- [29] Coutts, J. A., Mills, T. C. and Roberts, J. (1994), The Market Model and the Event Study Method: A Synthesis of the Econometric Criticisms, *International Review of Financial Analysis*, Vol. 3, No. 2, 149-171.
- [30] Dann, L. Y. and Mikkelsen, W. H. (1984), Convertible Debt Issuance, Capital Structure Change and Financing-Related Information, *Journal of Financial Economics*, Vol. 13, 157-186.
- [31] Davies, P. L. and Canes, M. (1978), Stock Prices and the Publication of Second Hand Information, *Journal of Business*, Vol. 51, 43-56.
- [32] Diebold, F. X. and Yilmaz, K. (2012), Better to give than to receive: Predictive directional measurement of volatility spillovers, *International Journal of Forecasting*, Vol. 28, No. 1, 57-66.
- [33] Diebold, F. X. and Yilmaz, K. (2014), On the network topology of variance decompositions: Measuring the connectedness of financial firms, *Journal of Econometrics*, Vol. 182, No. 1, 119-134.
- [34] Doumbia, D. and Haq, I. (2022), Structural Loopholes in Sustainability-Linked Bonds, *World Bank Policy Research Paper*, No. 10200.
- [35] Duan, T., Li, F. W. and Wen, Q. (2023), Is Carbon Risk Priced in the Cross Section of Corporate Bond Returns?, *Journal of Financial and Quantitative Analysis*, Vol. 60, No. 1, 1-35.
- [36] Dutta, A., Boui, E. and Noor, M. H. (2021), Climate bond, stock, gold, and oil markets: Dynamic correlations and hedging analyses during the COVID-19 outbreak, *Resources Policy*, Vol. 74, 102265.

- [37] Eccles, R. G., Ioannou, I. and Serafeim, G. (2014), The impact of corporate sustainability on organizational process and performance, *Management Science*, Vol. 60, No. 11, 2835–2857.
- [38] Eckbo, B. E. (1986), Valuation Effects of Corporate Debt Offerings, *Journal of Financial Economics*, Vol. 15, 119-151.
- [39] Eckbo, B. E., Masulis, R. W. and Noli, O. (2007), Security offerings. In: Eckbo, B. E. (Ed.), *Handbooks in Finance: Handbook of Empirical Corporate Finance*. Elsevier/Amsterdam, 233-373.
- [40] Ehlers, T. and Packer, F. (2017), Green bond finance and certification, *BIS Quarterly Review*.
- [41] Enel (2019), Enel launches the world’s first “general purpose SDG-linked bond”, successfully placing a 1.5 billion U.S. dollar bond on the U.S. market.
- [42] Engle, R. (2002), Dynamic Conditional Correlation A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models *Journal of Business & Economic Statistics*, Vol. 20, No. 3, 339-350.
- [43] Engle, R. F., Giglio, S., Kelly, B., Lee, H. and Stroebe, J. (2020), Hedging Climate Change News, *The Review of Financial Studies*, Vol. 33, No. 3, 1184-1216.
- [44] Erlandsson, U. and Mielnik, S. (2022), An option pricing approach for sustainability-linked bonds, *Anthropocene Fixed Income Institute Discussion Paper*.
- [45] Faccini, R., Matin, R. and Skiadopoulos, G. (2023), Dissecting climate risks: Are they reflected in stock prices? *Journal of Banking & Finance*, Vol. 155, 106948.
- [46] Fama, E. F., Fischer, L., Jensen, M. C. and Roll, R. (1969), The Adjustment of Stock Prices to New Information, *International Economic Review*, Vol. 10, No. 1, 1-21.
- [47] Fama, E. F. (1976), Efficient Capital Markets: Reply, *The Journal of Finance*, Vol. 31, No. 1, 143-145.
- [48] Fatica, S., Panzica, R., and Rancan, M. (2021), The pricing of green bonds: Are financial institutions special?, *Journal of Financial Stability*, Vol. 54, 2688–2701.
- [49] Ferrer, R., Shahzad, S. J. H. and Soriano, P. (2021), Are green bonds a different asset class? Evidence from time-frequency connectedness analysis, *Journal of Cleaner Production*, Vol. 292, 125988.

- [50] Flammer, C. (2021), Corporate Green Bonds, *Journal of Financial Economics*, Vol. 142, No. 2, 499-516.
- [51] Fong, K.Y.L., Holden, C.W., and Trzcinka, C.A. (2017), What are the best liquidity proxies for global research?, *Review of Finance*, Vol. 21, No. 4, 1355–1401.
- [52] Gabauer, D. and Stenfors, A. (2024), Quantile-on-quantile connectedness measures: Evidence from the US treasury yield curve, *Finance Research Letters*, Vol. 60, 104852.
- [53] Gianfrate, G. and Peri, M. (2019), The green advantage: Exploring the convenience of issuing green bonds, *Journal of Cleaner Production*, Vol. 219, 127–135.
- [54] Giraldez, J. and Fontana, S. (2022), Sustainability-linked bonds: The next frontier in sovereign financing, *Capital Markets Law Journal*, Vol. 17, No. 1, 8–19.
- [55] Godlewski, C. J., Turk-Ariss, R. and Weill, L. (2013), Sukuk vs. conventional bonds: A stock market perspective, *Journal of Comparative Economics*, Vol. 41, 745-761.
- [56] Hachenberg, B. and Schiereck, D. (2018), Are green bonds priced differently from conventional bonds?, *Journal of Asset Management*, Vol. 19, No. 6, 371–383.
- [57] Hartzmark, S.M. and Sussman, A.B. (2019), Do investors value sustainability? A natural experiment examining ranking and fund flows, *Journal of Finance*, Vol. 74, No. 6, 2789–2837.
- [58] Haq, I.U. and Doumbia, D. (2022), Structural Loopholes in Sustainability-Linked Bonds, *World Bank Policy Research Paper*.
- [59] Hsu, P.H, Li, K. and Tsou, C. Y. (2023), The Pollution Premium, *The Journal of Finance*, Vol. 78, No. 2, 1343-1392.
- [60] Huynh, T. D. and Xia, Y. (2021), Climate Change News Risk and Corporate Bond Returns, *Journal of Financial and Quantitative Analysis*, Vol. 56, No. 6, 1985-2009.
- [61] ICMA (2020), Sustainability-Linked Bond Principles, *International Capital Market Association*.
- [62] ICMA (2023), “Sustainability-Linked Bond Principles”, *International Capital Markets Association*.
- [63] In, S. Y., Park, K. Y. and Monk, A. (2019), Is Being Green Rewarded in the Market?: An Empirical Investigation of Decarbonization and Stock Returns, *Stanford Working Paper*.

- [64] Jin, J., Han, L. and Zeng, H. (2020), The hedging effect of green bonds on carbon market risk, *International Review of Financial Analysis*, Vol. 71, 101509.
- [65] Kapraun, J., Latino, C., Scheins, C. and Schlag, C. (2021), (In)-Credibly Green: Which Bonds Trade at a Green Bond Premium?, *Paris December 2019 Finance Meeting Proceedings*.
- [66] Karpf, A. and Mandel, A. (2018), The changing value of the green label on the US municipal bond market, *Nature Climate Change*, Vol. 8, No. 2, 161–168.
- [67] Klassen, R. and McLaughlin, C. (1996), The Impact of Environmental Management on Firm Performance, *Management Science*, Vol. 42, 1199-1214.
- [68] Kölbel, J. F. and Lambillon, A. P. (2022), Who pays for sustainability? An analysis of Sustainability-Linked Bonds, *Swiss Finance Institute Research Paper*.
- [69] Koop, G., Pesaran, H. H. and Potter, S. M. (1996), Impulse response analysis in nonlinear multivariate models?, *Journal of Econometrics*, Vol. 74, No. 1, 119-147.
- [70] Kroner, K. F. and Ng, V. K. (1998), Modeling Asymmetric Comovements of Asset Returns?, *The Review of Financial Studies*, Vol. 11, No. 4, 817-844.
- [71] Krueger, P. (2015), Corporate Goodness and Shareholder Wealth, *Journal of Finance and Economics*, Vol. 115, No. 2, 304–329.
- [72] Krueger, P., Sautner, Z. and Starks, L. T. (2020), The Importance of Climate Risks for Institutional Investors, *The Review of Financial Studies*, Vol. 33, No. 3, 1067-1111.
- [73] Larcker, D.F. and Watts, E. (2020), Where’s the Greenium?, *Journal of Accounting and Economics*, Vol. 69, 1–26.
- [74] Lebel, M., Jarjir, S. L. and Sassi, S. (2020), Corporate Green Bond Issuances: An International Evidence, (2020), *Journal of Risk and Financial Management*, Vol. 13, No. 25.
- [75] Liberadzki, M., Jaworski, P., and Liberadzki, K. (2021), Spread analysis of the sustainability-linked bonds tied to an issuer’s greenhouse gases emissions reduction target, *Energies*, Vol. 14, 1–12.
- [76] Libertore, S.M. (2021), Sustainability-Linked Bonds do not fit our impact framework, *Nuveen White Paper*.
- [77] Liu, P. S., Smith, D. and Syed, A. A. (1990), Stock Price Reaction to the Wall Street Journal’s Securities Recommendation, *Journal of Financial and Quantitative Risk Analysis*, Vol. 25, 399-410.

- [78] Liu, N., Liu, C. Zjang, B. T. and Guan, F. (2021), Dependence and risk spillovers between green bonds and clean energy markets, *Journal of Cleaner Production*, Vol. 279, 123595.
- [79] MacKinlay, C. A. (1997), Event Studies in Economics and Finance, *Journal of Economic Literature*, Vol. 35, 1-39.
- [80] Maino, A. (2022), Sustainability-Linked Bonds and their role in energy transition, *Oxford Institute for Energy Studies*.
- [81] Masulis, R. W. and Korwar, A. N. (1986), Seasoned Equity Offerings: An Empirical Investigations, *Journal of Financial Economics*, Vol. 15, 91-118.
- [82] McWilliams, A. and Siegel, D. (1997), Event Studies in Management Research: Theoretical and Empirical Issues, *Academy of Management Journal*, Vol. 40, No. 3, 626-657.
- [83] Merton, R. C. (1973), An Intertemporal Capital Asset Pricing Model, *Econometrica*, Vol. 41, No. 5, 867-887.
- [84] Mikkelsen, W. H. and Partch, M. M. (1985), Valuation Effects of Security Offerings and the Issuance Process, *Journal of Financial Economics*, Vol. 15, 31-60.
- [85] Miller, E. M. (1977), Risk, Uncertainty, and Divergence of Opinion, *The Journal of Finance*, Vol. 32, No. 4, 1151-1168.
- [86] Modigliani, F. and Miller, M. H. (1958), The Cost of Capital, Corporation Finance and the Theory of Investment, *The American Economic Review*, Vol. 48, No. 3, 261-297.
- [87] Naeem, M. A., Farid, S. Ferrer, R. and Shahzad, S. J. (2021), Comparative efficiency of green and conventional bonds pre- and during COVID-19: An asymmetric multifractal detrended fluctuation analysis, *Energy Policy*, Vol. 153, 112285.
- [88] Nelson, C. R. and Siegel, A. F. (1987), Parsimonious Modeling of Yield Curves, *The Journal of Business*, Vol. 60 No. 4, 473-489.
- [89] Nguyen, T. T. H., Naeem, M. A., Balli, F., Balli, H. O. and Vo. X. V. (2021), Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds, *Finance Research Letters*, Vol. 40, 101739.
- [90] Pastor, L., Stambaugh, R. F. and Taylor, L. A. (2021), Sustainable investing in equilibrium, *Journal of Financial Economics*, Vol. 142, No. 2, 550-571.

- [91] Pedersen, L.H., Fitzgibbons, S., and Pomorski, L. (2021), Responsible investing: The ESG-efficient frontier, *Journal of Financial Economics*, Vol. 142, No. 2, 572–597.
- [92] Pesaran, H. H. and Shin, Y. (1998), Generalized impulse response analysis in linear multivariate models? *Economics Letters*, Vol. 58, No. 1, 17-29.
- [93] Pietsch, A. and Salakhova, D. (2022), Pricing of green bonds: Drivers and dynamics of the greenium, *ECB Working Paper Series No. 2728*.
- [94] Pham, L. (2016), Is it risky to go green? A volatility analysis of the green bond market, *Journal of Sustainable Finance & Investment* , Vol. 6, No. 4, 263-291.
- [95] Pham, L. (2021), Frequency connectedness and cross-quantile dependence between green bond and green equity markets, *Energy Economics*, Vol. 98, 105257.
- [96] Pham, L and Cepni, O. (2022), Extreme directional spillovers between investor attention and green bond markets, *International Review of Economics & Finance* , Vol. 80, 186-210.
- [97] Pham, L. and Nguyen, C. P. (2021), Asymmetric tail dependence between green bonds and other asset classes, *Global Finance Journal*, Vol. 50, 100669.
- [98] Poggensee, J. (2025), The Pricing of Sustainability-Linked Bonds on the Primary and Secondary Bond Market. *Journal of Asset Management*, 1-21.
- [99] Reboredo, J. C. (2018), Green bond and financial markets: Co-movement, diversification and price spillover effects, *Energy Economics*, Vol. 74, 38-50.
- [100] Reboredo, J. C. and Ugolini, A. (2020), Price connectedness between green bond and financial markets, *Economic Modelling*, Vol. 88, 25-38.
- [101] Reboredo, J. C. and Ugolini, A. and Aiube, F. A. L. (2020), Network connectedness of green bonds and asset classes, *Energy Economics*, Vol. 86, 104629.
- [102] Reznick, M., Usson, R., and Demare, S. (2022), Do Sustainability-linked bonds have a step-up problem?, *Hermes International White Paper*.
- [103] Saeed, T., Bouri, E. and Tran, D. K (2020), Hedging Strategies of Green Assets against Dirty Energy Assets, *energies*, Vol. 13, 3141.
- [104] Seltzer, L. H., Starks, L. and Zhu, Q. (2022), Climate Regulatory Risk and Corporate Bonds, *NBER Working Paper*, No. 29994.
- [105] Sun, C., Xu, J. and You, Y. (2021), Physical Climate Change Exposure and Stock Returns, *Working Paper*.

- [106] Svensson, L. E. O. (1994), Estimating and Interpreting Forward Interest Rates: Sweden 1992-1994, *NBER Working Paper*, Working Paper No. 4871.
- [107] Tang, D. Y. and Zhang, Y. (2020), Do shareholders benefit from green bonds?, *Journal of Corporate Finance*, Vol. 61, 101427.
- [108] Tuhkanen, H. and Vulturius, G. (2020), Are green bonds funding the transition? Investigating the link between companies' climate targets and green debt financing, *Journal of Sustainable Finance & Investment*, Vol. 12, No. 4, 1194–1216.
- [109] Velte, P. (2022), Meta-analyses on Corporate Social Responsibility (CSR): a literature review, *Management Review Quarterly*, Vol. 72, 627-675.
- [110] Vishwanathan, P., van Oosterhout, H., Heugens, P., Duran, P. and van Essen, M. (2020), Strategic CSR: A Concept Building Meta-Analysis, *Journal of Management Studies*, Vol. 57, No. 2, 313-350.
- [111] Vulturius, G., Maltais, A., and Forsbacka, K. (2022), Sustainability-Linked Bonds—Their potential to promote issuers' transition to net-zero emissions and future research directions, *Journal of Sustainable Finance and Investment*, Vol. 14, 116–127.
- [112] Yousaf, I., Suleman, T. and Demirer, R. (2022), Green Investments: A Luxury Good or a Financial Necessity? *Energy Economics*, Vol. 105, 105745.
- [113] Zerbib, O. D (2019), The effect of pro-environmental preferences on bond prices: Evidence from green bonds, *Journal of Banking and Finance*, Vol. 98(C), 39-60.
- [114] Zhou, X. and Cui, Y. (2019), Green Bonds, Corporate Performance and Corporate Social Responsibility, *Sustainability*, Vol. 11, 6881.

Erklärung zum selbständigen Verfassen der Arbeit:

Ich erkläre hiermit, dass ich meine Doktorarbeit „*Essays on Sustainable Finance*“ selbstständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen meiner Arbeit, besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert habe.

Ort, Datum:

Unterschrift: