POLITECNICO
MILANO 1863

SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

Is There an ESG Premium in the Corporate Bond Market?

Tesi di Laurea Magistrale in
Mathematical Engineering - Quantitative Finance

Author: **Poli Riccardo**

Student ID: 968907
Advisor: Prof. Daniele Marazzina
Co-advisor: Prof. Aldo Nassigh
Academic Year: 2022-2023

Abstract

Climate change is one of the most pressing challenges of our time, posing significant risks to both human and natural systems. Thus, there is growing interest in addressing the problem through sustainable finance, which refers to the integration of Environmental, Social, and Governance (ESG) considerations into investment decisions, and seeks to redirect capital flows towards activities and projects that have a positive environmental impact.

This thesis has been conducted in conjunction with an internship at a major European Bank, whose focus has been on bond valuation in a risk management perspective.
The main goal of this research is to investigate the role of corporate ESG bonds, a specific type of sustainable financial instrument, by means of refined Machine Learning techniques, which allowed me to perform quantitative analyses on a large amount of data collected through the tools provided by the Bank.

Throughout my thesis, a guiding research question has been whether an "ESG Premium" exists, as a monetary incentive that motivates investors to purchase ESG corporate bonds in lieu of traditional ones, or if sustainable finance remains grounded in investor ethics.
Despite the answer is affirmative, the results of my analyses are not entirely positive.
Indeed, my findings reveal a price differential that renders ESG corporate bonds convenient than their conventional peers. However, following a more detailed analysis, this difference appears to be the product of low-creditworthiness issuers strengthening their access to the capital market by engaging in ESG initiatives.
In doing so, these issuers seek to attract greater investor interest, but the possibility of implementing an opportunistic strategy makes it difficult to discern whether they are driven by a genuine commitment to sustainable finance.

Overall, the research emphasizes the need for greater scrutiny of the ESG landscape, as it is becoming increasingly clear that not all ESG initiatives may be as virtuous as they seem at first glance. By assessing the motivations behind such initiatives, investors could make more informed decisions and promote real progress in sustainable finance.

Keywords: Corporate Bond, ESG Premium, Machine Learning, Z-spread, Rating.

Sunto

Il cambiamento climatico è una delle sfide più urgenti del nostro tempo, in quanto comporta rischi significativi per i sistemi naturali e per la comunità. Di conseguenza, c'è un crescente interesse nell'affrontarlo attraverso la finanza sostenibile, che si riferisce all'integrazione di considerazioni ambientali, sociali e amministrative nelle decisioni di investimento e cerca di ridirigere i flussi di capitale verso attività e progetti che hanno un impatto ambientale e sociale positivo.

Questo lavoro di tesi, svolto in concomitanza con uno stage in una delle principali Banche europee, il cui tema principale è stato quello di gestire il rischio di valutazione del prezzo di bond, si concentra sul ruolo di una particolare tipologia di strumenti sostenibili: i bond ESG societari. Tale indagine è stata svolta per mezzo di tecniche di Machine Learning, che hanno permesso di effettuare delle analisi quantitative su una grande mole di dati raccolta grazie agli strumenti messi a disposizione dalla Banca.

La domanda che ha ispirato le analisi è stata: esiste un "ESG Premium", cioè un incentivo monetario che spinga gli investitori a comprare bond ESG, piuttosto che quelli convenzionali? In caso contrario, si avrebbe evidenza di come la finanza sostenibile sia ancora principalmente basata sull'etica degli investitori.
La risposta si rivelerà affermativa, ma non positiva: nelle mie analisi, infatti, dimostro che esiste un differenziale di prezzo che rende le obbligazioni societarie ESG più convenienti delle loro pari convenzionali, ma anche che potrebbe essere determinato dal fatto che gli emittenti di scarsa qualità si impegnano a sostenere progetti ambientali e sociali con lo scopo di rafforzare il proprio accesso ai finanziamenti.

Questi risultati sottolineano la necessità di una maggiore consapevolezza del panorama ESG, le cui iniziative possono non sempre essere virtuose come sembrano.
Valutando le motivazioni alla base di tali progetti, gli investitori potrebbero prendere decisioni più informate e promuovere un reale progresso nel campo della finanza sostenibile.

Parole chiave: Bond societari, premio ESG, Machine Learning, Z-Spread, Rating.

Contents

Introduction

According to the Intergovernmental Panel on Climate Change (IPCC), achieving the goal of limiting global warming to 1.5°C will require "rapid, far-reaching and unprecedented changes in all aspects of society" [30]. The financial system will play a critical role in facilitating the necessary investments to decarbonize the economy, by ensuring that financial flows are "consistent with a pathway towards low greenhouse gas emissions and climate-resilient development" [30].

There exist already several instruments on the market aimed at financing projects and initiatives related to environmental sustainability and social progress. However, it is unclear whether these are really attractive and worthwhile for investors or whether, so far, ESG (Environmental, Social and Governance) investments have been driven solely by the virtuousness of individuals. Seeking an answer to this question, by means of quantitative analyses, is the aim of this thesis project.

Geopolitical Context

In the last century, our planet has undergone a dramatic rise in temperature: $1.1°C$ since the pre-industrial period. If this exceeds $2°C$, the repercussions will be disastrous for life on earth: droughts, loss of biodiversity, extreme weather, to name but a few of the consequences.

For this reason, 196 countries all over the world ratified the Paris Agreement in 2015, thereby agreeing to keep the increase in global temperature below that critical threshold. Even, it has been set as an ambitious goal to stay below $1.5°C$: this is recognized as a crucial global target because, beyond this level, even small changes can lead to dramatic shifts in the Earth's entire life support system.

Another milestone in the fight against climate change was the United Nations (UN) Cli-

mate Change Conference in Glasgow (COP26), which was held in 2021, from October 31 to November 12 [36].
It brought together representatives of almost 200 states in the world, that produced the "Glasgow Climate Pact" through intense negotiations: countries reaffirmed the Paris Agreement goal of limiting the increase in the global average temperature, pursuing efforts to limit it to 1.5 $°C$, and stressed the urgency of action "in this critical decade," when carbon dioxide emissions must be reduced by 45 per cent to reach net zero around mid-century.
In perhaps the most contested decision, countries ultimately agreed to a provision calling for a phase-down of coal power and a phase-out of "inefficient" fossil fuel subsidies – two key issues that had never been explicitly mentioned in decisions of UN climate talks before, despite coal, oil and gas being the main drivers of global warming.

Developed countries came to Glasgow falling short on their promise to deliver US$100 billion a year for developing countries. Voicing "regret," they reaffirms in the Glasgow outcome the pledge and urges to fully deliver on the goal urgently, expressing confidence that the target would be met in 2023.
However, as of 24 February 2022, a tragic event upset the world geopolitical balance: Russia's invasion of Ukraine. The entire Western world stood firmly by Ukraine's side, but this caused Russia to cut off gas and oil supplies and a subsequent energy crisis started, with the prices of these commodities skyrocketing.
In such a context, the fight against climate change was necessarily put on the back burner, as Europe slowed its transition from fossil fuels in the scramble for alternatives to Russian energy.

In the run-up to the COP27 summit, which took place in Sharm el-Sheikh in November 2022, it had been suggested that geopolitical crises, soaring inflation and a looming economic recession could distract policymakers from taking measures to avoid the worst effects of human-induced climate change. Despite U.K. Prime Minister Rishi Sunak's declarations about the fact that Russian President Vladimir Putin's "abhorrent war in Ukraine and rising energy prices across the world are not a reason to go slow on climate change. They are a reason to act faster (...) because diversifying our energy supplies by investing in renewables is precisely the way to insure ourselves against the risks of energy dependency", and French President Emmanuel Macron's promise that "We will not sacrifice our climate commitments under the energy threat from Russia and therefore all of the commitments made by nations must be held", a flurry of major UN reports delivered a bleak assessment of how close the planet is to irreversible climate breakdown, warning there is “no credible pathway” in place to cap global heating at $1.5°C$ [16].

As a matter of facts, Russia’s invasion of Ukraine has threatened to derail the decarbonization goals. Some European governments have been prompted to reconsider coal, one of the dirtiest and most polluting ways of producing energy, following a sustained period of reduced flows of Russian gas.
Germany, Italy, Austria and the Netherlands have all indicated that coal-fired plants could be used in the short term to compensate for a cut in Russian gas supplies.
European countries have also announced plans to build new liquefied natural gas terminals and extend the region’s network of gas pipelines.

Here is a graph, made by International Energy Agency (IEA)[1], which reports on the Global Coal consumption starting from 2000, with projections until 2025, and shows a worrying European increase from 392 Mt (Megatone) in 2020 to 478 Mt in 2022, with an almost constant projection in 2023.

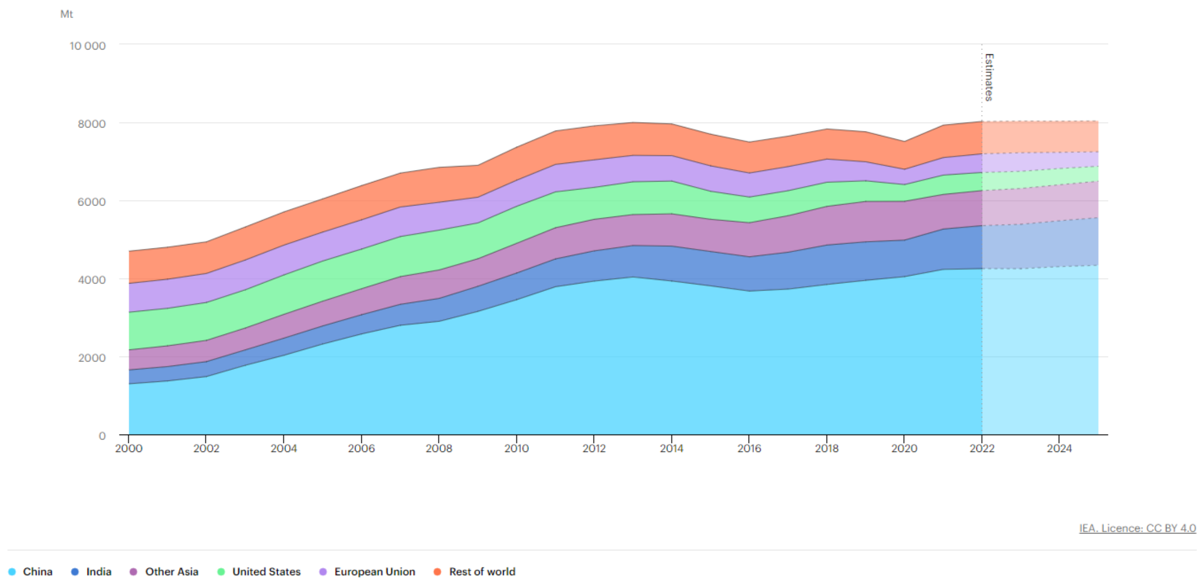


Figure 1: Global coal consumption, 2000-2025

Against such a tumultuous geopolitical backdrop, it is interesting to study the position of the financial markets towards climate and social investments, in order to verify by means of quantitative analyses whether this topic is indeed central and withstands huge global shocks, such as this tremendous war in Ukraine.

[1]IEA, Global coal consumption, 2000-2025, IEA, Paris (IEA. Licence: CC BY 4.0). [24]

Corporate Bonds

To pursue this goal, I selected a specific type of financial instrument as the object of my analyses: corporate bonds, divided between "ESG" and "non ESG" (or conventional).

A bond is a basic financial instrument that represents the debt of its issuer, while corporate bonds are a specific type of bonds which are issued by firms, not by governments. For a detailed description of such kind of instrument, please look at Appendix A: *"What Is A Bond?"*, while for more information about ESG bonds see Section 0.3: *"ESG Bond Market"*

In general, bonds are considered to be more conservative investments than stocks, since they are more senior in case of issuer's bankruptcy. Bonds also typically pay regular interest payments to investors, and return the full principal loaned when the bond matures: this is why they are typically referred as "fixed-income" assets.
The bond markets are very liquid and active, still bond prices tend to be less volatile than stocks and they are often more receptive to interest rate changes than other market conditions. Bond prices vary inversely with interest rates: as rates rise, bond prices fall, and vice-versa.

For all the features just listed, these financial instruments represent a reliable means of describing market trends in an environment of such high volatility and uncertainty as the one in which the analyses performed below are placed.
The performance of bonds is often considered as a good indicator of future economy short-term behaviour [32]. The reason is that bond markets are mainly driven by future trends of monetary policies drafted by Central Banks, thus its impact on the outlook for interest rates is considered as a way to see how the economy might fare in the coming years.
The decision to focus only on corporate bonds is instead dictated by the fact that, in such an uncertain and strained geopolitical environment, the performance of government bonds could be too influenced by external news and events and no longer reflect market trends.

ESG Bonds

Environmental, Social and Governance (ESG) Bonds are a relatively new type of bonds, introduced in 2007 by European Investment Bank (EIB) and defined by the International Capital Markets Association (ICMA) Sustainable Finance principles [20].

In particular, four different categories of bonds will fall under the "ESG" label:

- **Green bonds** [19] that "enable capital-raising and investment for new and existing projects with environmental benefits". "The Green Bond Principles (GBP) seek to support issuers in financing environmentally sound and sustainable projects that foster a net-zero emissions economy and protect the environment. GBP-aligned issuance should provide transparent green credentials alongside an investment opportunity. By recommending that issuers report on the use of Green Bond proceeds, the GBP promote a step change in transparency that facilitates the tracking of funds to environmental projects, while simultaneously aiming to improve insight into their estimated impact".
- **Social bonds** [22] that "are use of proceeds bonds that raise funds for new and existing projects with positive social outcomes". "The Social Bond Principles (SBP) seek to support issuers in financing socially sound and sustainable projects that achieve greater social benefits. SBP-aligned issuance should provide transparent social credentials alongside an investment opportunity. By recommending that issuers report on the use of Social Bond proceeds, the SBP promote a step change in transparency that facilitates the tracking of funds to social projects, while simultaneously aiming to improve insight into their estimated impact".
- **Sustainability bonds** [21] for which "the proceeds will be exclusively applied to finance or re-finance a combination of both green and social projects".
- **Sustainability-linked bonds** [23] which "aim to further develop the key role that debt markets can play in funding and encouraging companies that contribute to sustainability (from an environmental and/or social and/or governance perspective)".

To sum up, ESG bonds are just conventional bonds, but with an additional and distinguishing feature: the funds raised through them are injected into projects that have a positive impact on combating environmental deterioration or to face social challenges.

The evolution of ESG Bonds market over the last years confirms the tremendous potential of this financial instrument. Indeed, since the EIB issued the first Green bond in 2007, the market has kept growing and becoming more sophisticated.

Sustainable debt volumes exceed USD 1.6 trillion in 2021 alone, more than doubling the year-end value of 2020. These are the figures released by research firm BloombergNEF in its 1H 2022 Sustainable Finance Market Outlook [1].

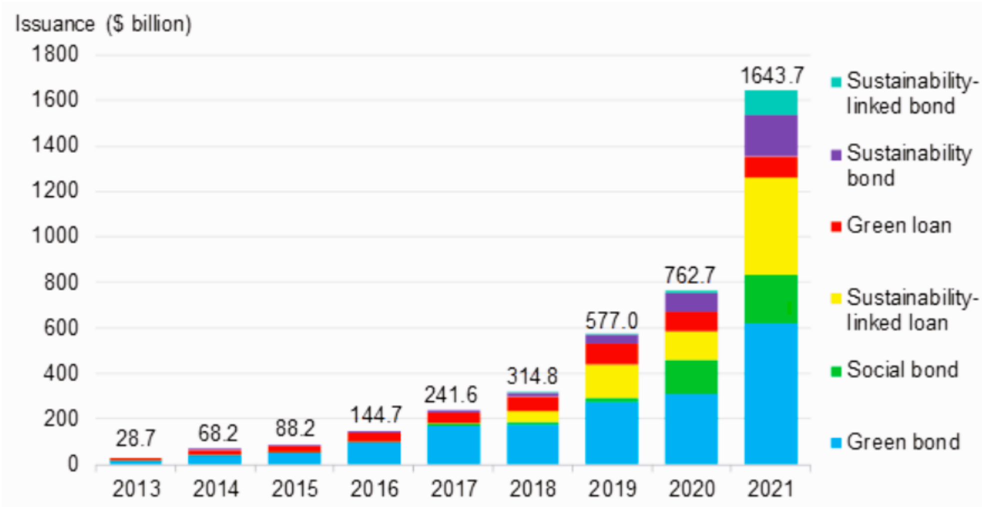


Figure 2: Annual Sustainable Debt Issuance, 2013-2021.
Source: *BloombergNEF*, *Bloomberg L.P.*

Although the ESG Bond market has shown impressive growth in recent years, it is evident that a 1.6 trillion US$ market is by far not enough to address the global sustainability challenges and provide the capital at scale urgently needed for the necessary transformation. Compared to 100 trillion US$ global fixed income market, the ESG bond market is still a small but shiny light.

The IPCC report is an alarming warning and it implicitly confirms the unprecedented investment opportunity that can be unlocked when sustainable finance becomes mainstream. With banks having restricted lending capabilities and public budgets under strain in many countries, private sector sources of capital need to be engaged and green bonds are considered among the key instruments to mobilize private financial resources towards the progressive decarbonisation of the global economy (OECD, 2017).

While the relevance of green bonds is widely recognized by financial professionals, little is known either about the convenience of ESG bonds issuance, for corporate and non-corporate institutions, and even less about the convenience of buying this kind of bonds rather than conventional ones, from the investor perspective.

Data Overview, Research Question and Methodology

In order to understand the distinguishing features of ESG bonds, with respect to Conventional ones, I focused on a precise financial quantity: the Z-spread.

The Z-spread is defined as the constant spread that makes the price of a security equal to the present value of its cash flows when added to the yield at each point on the spot rate Treasury curve, where a cash flow is received.
For more details about its definition, interpretation and computation, please look at Appendix A: *"Bonds' Z-Spread"*.

The fundamental feature of this quantity, that I have exploited in my analyses, is the fact that the Z-spread can, neglecting the liquidity risk by choosing only highly liquid bonds, be interpreted as measure of the credit risk of the bond itself, i.e. the risk that the instrument will not repay its owner. There exists an inverse relationship between Z-spread and price: the more likely it is that the bond will not repay, the higher its Z-spread and the lower its value, and thus its price.
However, this relationship is not so accurate because of the many external factors that influence the price, especially in a tumultuous environment like the one in which my analyses take place: for this reason, I will focus uniquely on the Z-spread.

This thesis work has been done concurrently with an internship in a major European Bank, which provided me with several tools thanks to which I have been able to collect and analyze a large amount of bonds data.
In particular, through a cross-search between Bloomberg and internally developed tools of the Bank, I collected 897 bonds, all characterised by a high liquidity and balanced between ESG and non-ESG classes, then I retrieved their time series of prices, Z-spreads, outstanding capital amounts and ratings.

My first objective was to verify whether there exists a systematic difference between ESG and non ESG bonds' Z-spreads. This being the case, I try to explain this delta through quantitative analyses, in particular I use:

- a time series analysis, both a graphical one and one on structural break points;
- a logistic regression, used for binary classification for two Z-spreads classes;
- a neural network, used for multiple classification for four Z-spreads classes.

Chapters Outline

The subsequent chapters of this thesis provide an in-depth exploration of the topic at hand. The chapter breakdown is as follows:

- *Chapter 1*: "Literature Review", offers a comprehensive summary of existing research on topics related to the subject matter, providing valuable insights and identifying potential areas for further investigation.
- *Chapter 2*: "Data Collection and Exploration", provides a detailed account of the data collection process, as well as the pre-processing techniques employed to ensure the data is suitable for analysis using the adopted models.
- *Chapter 3*: "Time Series Analysis", presents graphical inspections and qualitative considerations of the data, drawing preliminary conclusions that are further investigated using quantitative analysis techniques.
- *Chapter 4*: "Classification Algorithms", outlines the theoretical foundations of the machine learning techniques used throughout the study.
- *Chapter 5*: "Results", offers a thorough description of the algorithms employed, presenting detailed results and findings.
- *Chapter 6*: "Conclusions and Future Developments", provides a comprehensive overview of the study's outcomes and identifies potential avenues for further research and improvement.

The thesis also contains an appendix at the end, named "What Is a Bond?" (*Appendix A*), the purpose of which is to describe in detail the financial instrument that is the subject of my research.

1 | Literature Review

ESG bonds have gained popularity in recent years, starting from the first Green bond issued in 2007, but the available scientific literature on the topic is still limited.
Investors are presented with an explicit opportunity to invest in climate-protecting and society-advancing projects through the growing market of ESG bonds. However, it remains uncertain whether this emerging asset class offers risk-return profiles that are as attractive as those of conventional bonds.

In a study conducted by Zerbib [39], 135 investment grade green bonds revealed a small negative premium, whereby the yield of green bonds was lower than that of conventional bonds. The average premium across the entire sample was -2 basis points, with financial and low-rated bonds exhibiting a more pronounced effect. The findings highlight that investors' pro-environmental preferences have a minimal impact on bond prices, which currently does not discourage them from supporting the growth of the green bond market.

The research conducted by Gianfrate and Peri [17] adds to the existing literature by presenting evidence of a significant advantage for European green bonds in the primary market, which is found to persist in the secondary market after issuance. The analysis was conducted on 121 European green bonds, issued between 2013 and 2017, which were associated to conventional bonds with similar characteristics. It revealed that green bonds are financially more convenient than non-green ones from the issuer perspective, with the advantage being greater for corporate ones. These findings provide support for the idea that green bonds have the potential to promote a greener economy without imposing a financial burden on issuers.

Hachenberg and Schiereck [18] revealed that green bonds with rating classes among AAA and BBB are traded with slightly lower margins[1] compared to non-green bonds issued by the same entities during the same period.
Additionally, financial and corporate green bonds have narrower trading margins compared to their corresponding non-green bonds, while government-related green bonds exhibit marginally wider margins. Differences in issue size, maturity, and currency did not have a substantial impact on pricing disparities; however, industry and ESG rating had a significant influence.

From this result, some kind of link between rating classes and the value of green bonds begins to emerge, which will indeed be central to my analyses.
However, in all the literature cited so far, one cannot distinctly identify an indicator that clarifies whether investing in ESG bonds is really worthwhile, from an investor's perspective.

From this inhomogeneity of judgment, the research conducted by MacAskill, Roca, Liu, Stewart, Sahin [31] arises. This is a systematic literature review to establish a consensus on the existence of a green premium in the bond market: it analyzed studies published between 2007 and 2019 and identified some green bond characteristics that are most likely to exhibit a "Greenium", which is defined as the "difference between the yields on a conventional bond and a green bond with the same characteristics" [14]. A 'Greenium' implies that the yield an investor is willing to accept for a 'green' asset is lower than that of conventional counterparts.
The findings suggest a consensus on the existence of a Greenium within 56% of primary and 70% of secondary market studies, particularly for government-issued, investment-grade [2] green bonds that follow defined governance and reporting procedures. The green premium varies widely in the primary market, but an average Greenium of -1 to -9 basis points on the secondary market is observed. The study highlights the importance of strengthening environmental preferences among bond market participants and suggests that future bond pricing should consider non-economic motives of investors.

[1] In Finance, "Margin" refers to the security deposit an investor must furnish to their broker or exchange in order to mitigate the credit risk associated with the investor's holdings. This credit risk can arise when the investor obtains cash from the broker to purchase financial instruments, borrows financial instruments for short selling purposes, or enters into a derivative contract.
Source: [4]

[2] "Investment grade" bonds are considered lower risk and more likely to be repaid with interest, thus credit rating agencies rate them as BBB- (Standard & Poor's and Fitch), or Baa3 (Moody's), or better.
Source: [2]

All the previously mentioned works do not take into account quantitative tools based on Artificial Intelligence (AI), which is actually the methodology I intend to use.

Çetin, D. T. [15] is the first to prove the effectiveness of a Multi-Layer Feed-Back Artificial Neural Network (MLF-ANN) model[3], applied to green bonds. In particular, the paper aims to forecast the corporate Green Bond index[4] value using an ANN model and to identify the predictor by addressing the conceptual framework of green bonds.
The MLF-ANN model is designed using S&P 500 bond index[5] values as input and S&P green bond index values as output.The study finds that the S&P green bond index values are forecasted with high precision and statistical significance:

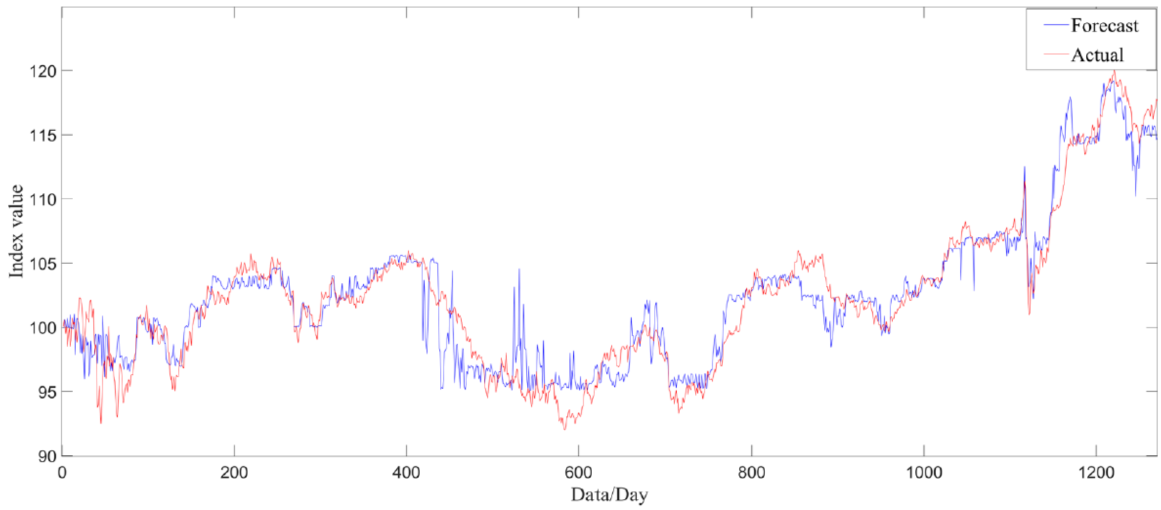


Figure 1.1: Forecasted and Actual S&P Green Bond Index Chart

[3]There have been two main structural paradigms developed for Artificial Neural Networks (ANNs):
- *Feed-Forward Neural Networks* are the most common ones, with data flowing in a single direction from input neurons to output ones (see Section 4.2: *"Artificial Neural Network"* for more details).
- *Feed-Back Neural Networks*, such as a Recurrent ones (RNN), feature feed-back paths, which allow signals to use loops to travel in both directions and render Feed-Back ANNs non-linear dynamic systems that evolve during training continually, until they achieve an equilibrium state.
Source: [6]

[4]The S&P Green Bond Index "is designed to track the global green bond market. This pioneering index maintains stringent standards in order to include only those bonds whose proceeds are used to finance environmentally friendly projects".
Source: [8]

[5]The S&P 500 Bond Index "is designed to be a corporate-bond counterpart to the S&P 500, which is widely regarded as the best single gauge of large-cap U.S. equities. Market value-weighted, the index seeks to measure the performance of U.S. corporate debt issued by constituents in the iconic S&P 500".
Source: [7]

Starting from the fact that there exists a correlation of about 70% between the two indexes, these results ensure that the trend of S&P Green Bond index, which comprises 9,953 corporate green bonds, can be predicted with great accuracy by S&P 500 Bond index. It is not specified in the text whether the unexplained 30% is to be attributed to idiosyncratic factors, i.e. differences in the baskets of the two indices in terms of geographic diversification, sector or rating class, or actually depends on the Green characteristic of the bonds composing the S&P Green Bond index.
Being able to forecast such a crucial green bond index, which operates on a large scale, can decrease uncertainty in green bond markets and serve as a benchmark for investors and market makers. Additionally, this index provides investors with significant advantages such as optimizing profits or minimizing losses.

Another research that applies Neural Networks to analyze Green Bonds is the one of Peters, Zhu, Tzougas, Rabitti, Ismaila[33]. Their aim is to apply a specialised form of Recurrent Neural Network, comprised of a Long Short Term Memory (LSTM) [6] feature embedding framework, to show that one can accurately interpret and forecast returns series for two leading green bond indices: the Bloomberg Barclays MSCI green bond index and the S&P green bond index.

Based on the current reported results, it appears that the primary focus of the researchers has been on predicting the future performance of green bonds, with the goal of providing investors with an immediate assessment tool for sustainable finance.
However, limited effort has been dedicated to comprehensively understanding the structural benefits of these bonds, as compared to conventional bonds.

As a result, the aim of this thesis is to utilize modern and robust Machine Learning and Deep Learning methodologies to address this inquiry, specifically by examining whether there exists a difference in value between ESG bonds, taken in a broad sense and not only focusing on green ones, and conventional bonds. Furthermore, this investigation will delve into the underlying factors that contribute to such differences, if any.

[6] Long Short Term Memory networks are a special kind of RNN, capable of learning long-term dependencies thanks to four special NN layers interacting in a particular manner. This is not a key point in my work, since I will not use this type of architecture in my analysis, thus no more details will be needed.

2 | Data Collection and Exploration

The first step in the data collection process was to search for all ESG bonds to which the bank has had some exposure from the beginning of 2021 up to the end of November 2022. With "ESG", I refer to all those bonds having at least one of the following Bloomberg "Debt Labels":

- **Green** Bond/Loan: Proceeds of the fixed income instrument will be applied toward green projects or activities that promote climate change mitigation or adaptation, or other environmental sustainability purposes;
- **Sustainable**: Proceeds will be applied toward projects that are dedicated to environmentally sustainable outcomes (a combination of green and social activities as eligible projects);
- **Social**: Proceeds will be applied toward projects that promote improved social welfare and positive social impact directly for underprivileged, low income, marginalized, excluded or disadvantaged populations;
- **Sustainability-Linked**: Proceeds where the terms of a fixed income security are aligned with the Company's (issuer/borrower) performance against relevant predetermined sustainability targets in order to boost their sustainability profile.

Then, I tried to trace the issuers of these ESG bonds so as to find non-ESG issues that were similar to ESG ones in terms of time-to-maturity, outstanding amount, coupon type, seniority, rating and currency, i.e. all those characteristics that, given the same issuer, are able to distinguish different bonds. The idea was is to find issuers as homogeneous as possible, in terms of ESG versus non-ESG bonds numerosity, so to have two balanced sub-samples.

The last selection step was to eliminate all illiquid bonds from my sample, so as to exclude any liquidity premiums from my analysis. To do this, I only considered bonds labelled with a Fair Value Hierarchy Level (FVHL) [1] equal to 1, i.e. all the most liquid bonds, having a lot of executable market quotes on a daily basis.

Once I had the list of ESG and non ESG bonds' International Securities Identification Numbering (ISIN), i.e. their identification code, for each single date in the period of interest, I started gathering the most meaningful information of these bonds: this process has been done by using the different banks' tools at my disposal, that allowed me to collect data about the bonds' features, the bonds' prices and implied spreads, and the bonds' issuers.
The Composite Bloomberg Bond Trader (CBBT) has been the primary source for obtaining end-of-day bond prices, due to their high liquidity. These prices are used as inputs in an internal Bank calculation engine to derive implied end-of-day Z-spreads[2] , which are then utilized in my analyses. In addition, all other bonds' term sheet information is sourced from Bloomberg as well, who in turn derive it from individual bonds' prospectuses.

The last step was the one of associating to each ISIN the ESG flag taken from Bloomberg. The label I chose to identify this feature takes the following values:

- 0, if the bond is a Conventional one ("Non ESG");
- 1, if the bond is a Green one;
- 2, if the bond is a Sustainable one;
- 3, if the bond is a Social one;
- 4, if the bond is a Sustainability-Linked one.

[1]The Fair Value Hierarchy Level (FVHL) is a financial metric used to classify the inputs used in determining the fair value of an asset or liability. It categorizes these inputs into three levels based on their degree of observability in the market:
Level 1 inputs are quoted prices in active markets for identical assets or liabilities that the entity can access at the measurement date.
Level 2 inputs are observable inputs other than quoted prices included in Level 1, such as prices for similar assets or liabilities, or prices in markets that are not active.
Level 3 inputs are unobservable inputs for the asset or liability, based on the entity's own assumptions about the assumptions market participants would use in pricing the asset or liability.
Therefore, the Fair Value Hierarchy Level represents the reliability and observability of the inputs used in determining the fair value of an asset or liability, with Level 1 inputs being the most reliable and observable, and Level 3 inputs being the least reliable and observable.

[2]See Appendix A *"Bonds' Z-spread"* for an example of Z-spread calculation.

2.1. Data Pre-Processing

Once the database was assembled, I cleaned it up before doing any kind of analysis on it. Specifically, the two data pre-processing operations performed were:

- the removal of those database rows not having a Z-spread[3] , since this is the main variable of my analysis and so missing Z-spread data would be useless at all;
- the removal of the empirical distribution tails of Z-spread data, performed by means of a confidence interval with level $\alpha = 1\%$.
  This step was necessary because, as I collected real market data, they were contaminated with outliers that increased the noise in my database, resulting in greater uncertainty in the results of my analyses.

Thanks to these operations, I ended up with a Z-spread variable which takes values from its minimum -47 to its maximum 623, with no missing values.

2.2. Final Database Composition

The final database contains 259'048 observations of 879 bonds, 476 of which are "Non ESG" and 403 are "ESG" (i.e. either Green, Sustainable, Social or Sustainability-Linked). These data span from "2021-01-04" to "2022-11-22", with every single bond having its own time series contained in this time interval and determined by all the dates in which an exposure of the bank to that bond have been recorded.
The succession of dates associated with the same bond determines the bond's time series, with attached all the bond's characteristic quantities that may evolve over time or remain constant.
The 29 variables I chose in order to describe in depth such bonds are:

- *As.of.Date*: business date of interest, it can span from January 4, 2021 to November 22, 2022. As mentioned above, having an "As.of.Date" for a specific bond means that, in that date, the Bank had a non-zero exposure on it.
- *ISIN*: alphanumeric code that identifies each bond.
- *Ask*: ask price, i.e. the End-of-Day (EoD) price at which the bond can be bought.
- *Bid*: bid price, i.e. the EoD price at which the bond can be sold.

[3]For more details about this crucial financial quantity, see Appendix A *"Bonds' Z-spread"*

- *Mid*: mid price, i.e. the arithmetic average between ask and bid prices.
- *Z.spread*: Z-spread of the bond, i.e. the implied spread that measures the credit worthiness of that specific instrument (not of its issuer).
  This is the key variable of my research, thus an ad-hoc chapter of Appendix A named *"Bonds' Z-spread"* is developed at the end of the document.
- *Executable*: flag that is true whether the contributor of the EoD price is willing to buy/sell that bond at those declared prices, false otherwise.
- *Comments*: specification of the End-of-Day pricing rule adopted for that specific date. Notice that this rule can change every day, even for the same bond, since its logic is to select the most reliable quotes of that specific date at market closure.
- *Stale.Period*: number of days in which the bond price has been stale, i.e. equal to the previous day one.
- *Synthetic.Stale*: flag that is true whether the staleness of the bond price is due to the fact that the contributors are not providing any market quote, on the contrary it is false if the bond price staleness is due to the fact that the contributor provided market quotes that are equal to the ones of the previous day.
- *Issuer*: the legal entity that issued the bond. In my analyses, only corporate bonds have been considered, i.e. those bonds issued by firms and not by governments.
- *CCY*: currency at which the bond has been issued.
  The eight CCYs represented in my dataset are: Euro (EUR), Australian Dollar (AUD), Canadian Dollar (CAD), Great British Pound (GBP), Indian Rupee (INR), Japanese Yen (JPY), US Dollar (USD), South Afrinca Rand (ZAR).
- *Issue.Type*: it can be either "Covered", "Pfandbriefe" ("Covered" in German language) or "Cedulas" ("Covered" in Spanish language), in the case in which the bond is Covered [4] , while it's empty ("") otherwise.
- *Maturity.Type*: it is empty (""), for conventional bonds, while it contains one of the following words if some specific features are connected to the bond:
  - "Callable", if the bond can be bought at a pre-estabilished date before maturity;
  - "Putable", if the bond can be sold at a pre-estabilished date before maturity;
  - "Perpetual", if the bond does not have a precise maturity date and so it pays a steady stream of interest;

[4] Covered bonds guarantee the repayment of principal and interest by tying up a portion of the bank's assets exclusively earmarked for the remuneration and repayment of the bond.

- "Convertible", if it yields interest payments but can be converted into a predetermined number of common stocks or equity shares.

Notice that the above characteristics are not mutually exclusive, thus they can coexist for a single bond.

- *Seniority*: the order of repayment in the event of a sale or bankruptcy of the issuer. In my database, bonds can be "Senior", if they're the first one to repay investors, or thay can have the following levels of subordination:
  - Tier I bonds ("T1"): in the presence of adverse management trends and in the event of liquidation, T1 bonds grant to their holders the privilege over ordinary shares and savings holders, but they are subordinate to all other claims.
  They represent the riskiest type of bonds; in the event that the bank does not pay dividends to shareholders, the coupon can be even cancelled.
  - Senior Non Preferred bonds ("Senior TLAC") [9]: Total Loss-Absorbing Capacity is an international standard, finalised by the Financial Stability Board (FSB) in November 2015, intended to ensure that global systemically important banks (G-Sibs) have enough equity and bail-in debt to pass losses to investors and minimise the risk of a government bailout.
  - Lower Tier II ("LT2") [5]: having maturities around 10 years, LT2 bonds represent one of the most privileged category within subordinated bonds. Indeed, coupons are locked in only in the event of a severe default.

- *Recovery.Rate*: the extent to which principal and accrued interest on defaulted debt can be recovered, expressed as a percentage of face value.
- *Issued.Amount*: the total amount of money (expressed in €) to be raised by the issuance of the bond.
- *Outstanding.Amount*: the amount of money (expressed in €) currently available on the market, with respect to the initially issued amount.
- *Legal.Maturity*: the date when the principal amount of the bond is typically repaid to the investor, along with the final interest payment.
- *Expected.Maturity*: the date when the principal amount of the bond is expected to repay, it may differ from the Legal one for "Callable", "Putable" and "Convertible" bonds.
- *Country.of.Risk*: it reflects the uncertainty inherent with investing within a given country, where the bond's issuer is physically located.

- *Coupon.Type*: it describes the coupon payment of the bond, i.e. the percentage of the face value paid from issuance to maturity. The different types of coupon are:
  - "ZERO-COUPON", if the bond has no coupons and so its yield is just determined by the difference between its issue value and its refund one, when it matures;
  - "FIXED", if the bond pays the same level of interest over its entire term;
  - "VARIABLE", if the bond's payments are adjusted at specific time intervals;
  - "FLOATER", if its interest payments are tied to a pre-determined benchmark index (e.g. Euribor);
  - "MULTI-COUPON", if the bond pays its coupons more often than conventional ones (e.g. quarterly).

- *Coupon*: the fixed amount of the annual interest rate paid by the bond, expressed as a percentage of the face value and paid from issue date until maturity. *Green.Flag* that is equal to 1 if the bond is ESG, 0 otherwise. This variable is not a real characteristic of a bond, it was added only to check how much the topic had already been studied in the context of the bank.

- *Rating*: rating of the bond, see the Section A.3: *"Credit Ratings"* of Appendix A for more details.

- *Rating.Source*: source of the previous *Rating* information, most ones coming from Standard & Poor's rating agency.

- *Term*: time-to-maturity of the bond, i.e. the number of years to its Legal Maturity.

- *Industry*: sector to which the bond's issuer belongs. In my database, the following sectors are considered: "Financial", "Basic Materials", "Government", "Utilities", "Consumer Cyclical", "Consumer Non cyclical", "Industrial", "Communications", "Energy".

- *ESG.Flag*: this flag reflects the Bloomberg categories for ESG bonds. As mentioned above, it is 0 if the Bond is Conventional ("Non ESG"), while it's equal to 1, if the bond is "Green", 2, if the bond is "Sustainable", 3, if the bond is "Social", or 4, if the bond is "Sustainability Linked".

- *IssuerRating*: rating of the issuer, it follows the same logic of single bonds ratings. See the Section A.3: *"Credit Ratings"* of Appendix A for more details.

2.3. Z-Spread Mean Distribution

As a first data inspection, it is useful to visualize the basic statistical quantities of Z-spread variable: mean and standard deviation. In particular, it's interesting to assign such values to each class of the main drivers of the Z-spread itself: Rating, Sector, Currency and ESG flag.

2.3.1. Rating

The expectation of the Z-spread mean distribution, with respect to the Rating of the single bonds, is that the better the rating is, the lower the Z-spread mean will be.
From the empirical data collected, this is what can be observed:

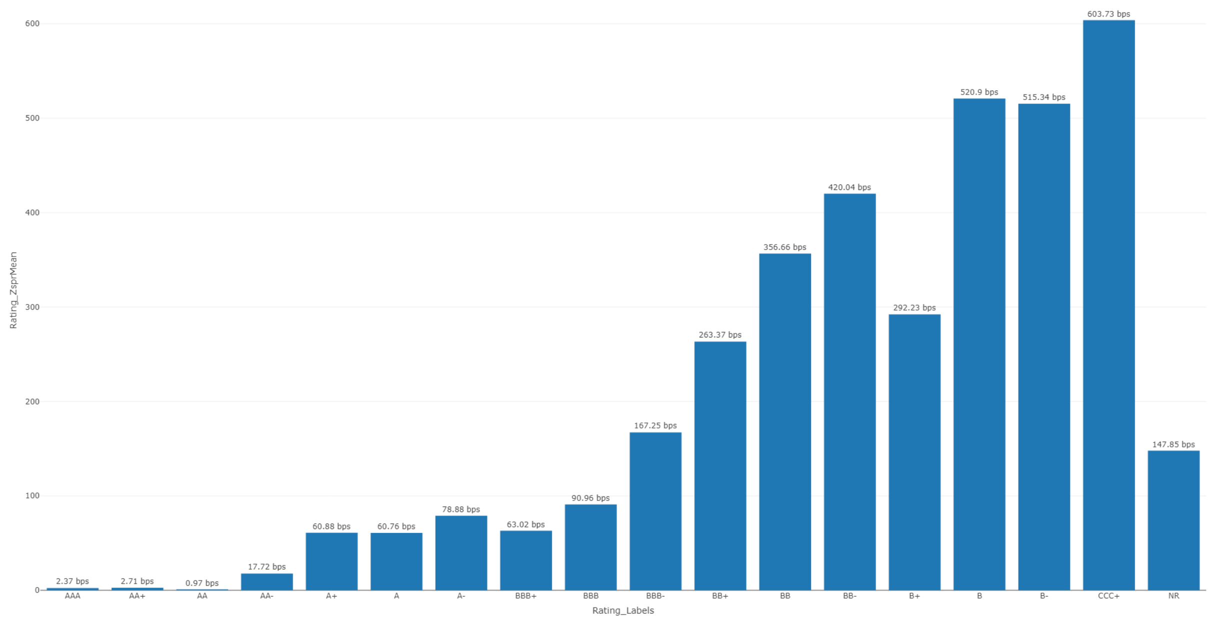


Figure 2.1: Z-spread Mean vs. Rating

As expected, there is an increasing trend of the Z-spread mean as the Rating gets worst. Obviously, since these are empirical data, this trend cannot be perfectly linear because of the unbalance of the various rating classes (see the following table to see the cardinality of each class).

Here are the basic statistical quantities of Z-spread, for each different Bond Rating: Numerosity, Mean, Standard Deviation (SD) and Standard Error (SE)

Bond Rating vs. Z-spread (bps)

Rating	N° bonds	Z-spread Mean	Z-spread SD	Z-spread SE
AAA	378	2.4	18.8	0.9
AA+	81	2.7	17.0	1.9
AA	41	0.9	9.9	1.6
AA-	29	17.7	26.9	4.9
A+	19	60.9	33.2	7.6
A	40	60.8	53.2	8.4
A-	54	78.9	66.8	9.1
BBB+	84	63.0	56.6	6.2
BBB	58	90.9	79.1	10.4
BBB-	48	167.2	121.9	17.6
BB+	14	263.4	108.4	28.9
BB	7	356.7	161.9	61.2
BB-	4	420.0	94.2	47.1
B+	3	292.2	103.3	59.7
B	3	520.9	67.8	39.2
B-	2	515.3	47.5	33.6
CCC+	1	603.7	4.1	4.1
NR	13	147.8	105.0	29.1

Table 2.1: Basic statistics: mean and standard deviation

2.3.2. Sector

In this case, the expectation is that the Z-spread mean is lower for the two most steady industries in the market: Government and Financial sectors.
Indeed, this guess is confirmed by empirical observations:

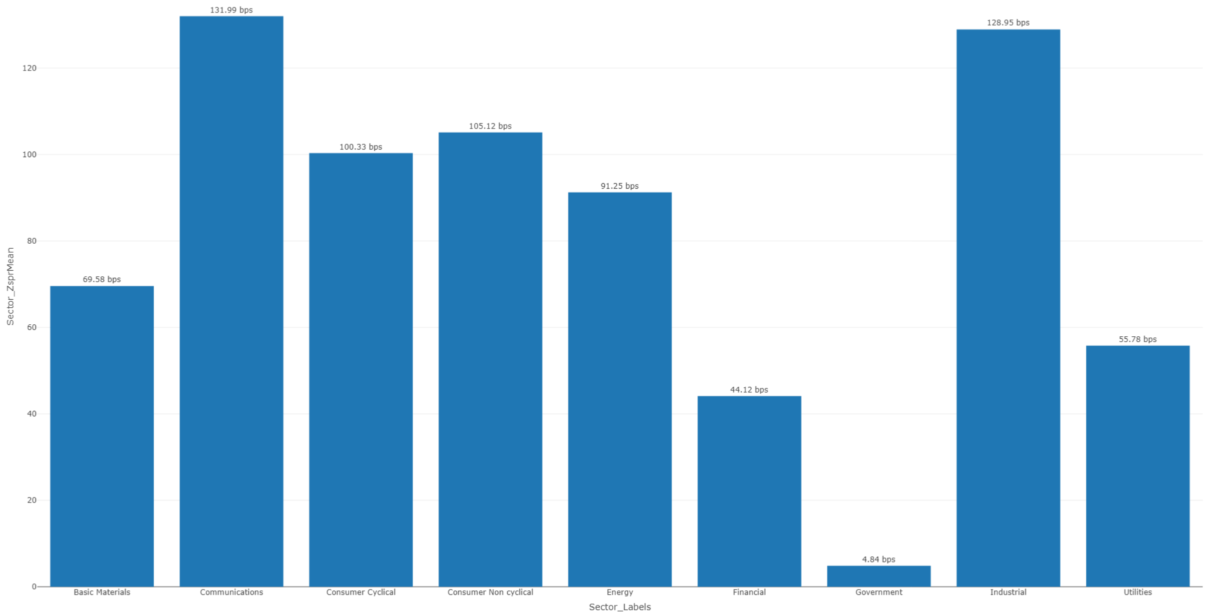


Figure 2.2: Z-spread Mean vs. Sector

Here follow the statistical quantities of Z-spread, with respect to each Sector:

Bond Sector vs. Z-spread (bps)

Sector	N° bonds	Z-spread Mean	Z-spread SD	Z-spread SE
Basic Materials	14	69.5	82.0	21.9
Communications	10	131.9	123.1	38.9
Consumer Cyclical	30	100.3	107.3	19.6
Consumer Non Cycl.	15	105.1	90.9	23.5
Energy	17	91.2	99.8	24.2
Financial	476	44.1	97.0	4.4
Government	187	4.8	23.6	1.7
Industrial	24	128.9	158.2	32.3
Utilities	106	55.8	54.4	5.3

Table 2.2: Basic statistics: mean and standard deviation

2.3.3. Currency

Here is the Z-spread mean distribution with respect to bonds' Currency (CCY):

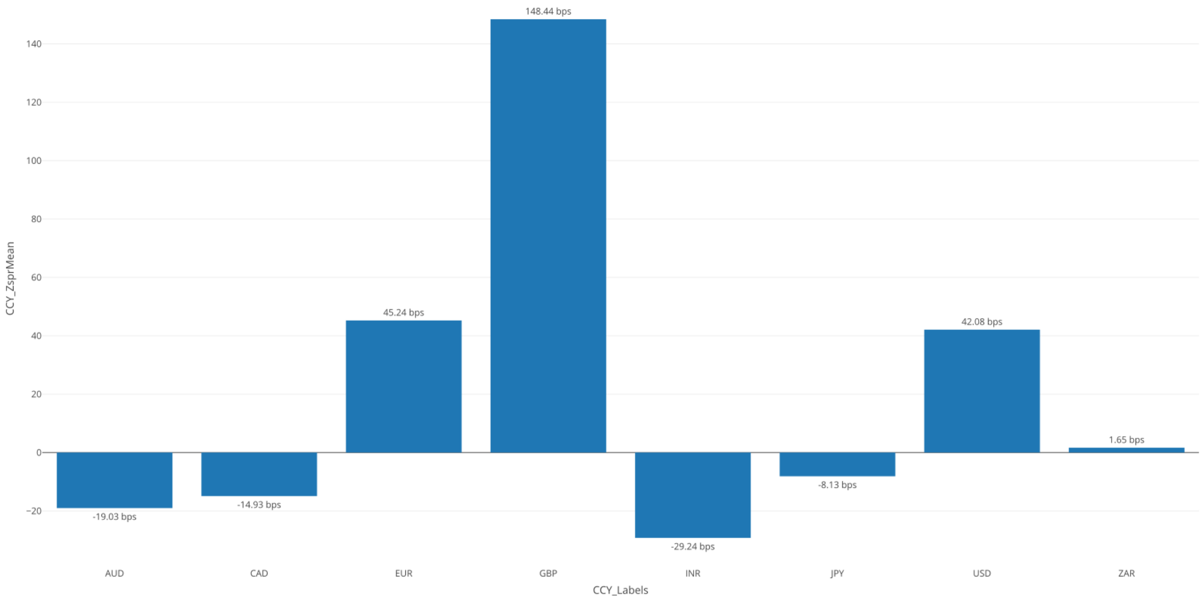


Figure 2.3: Z-spread Mean vs. Currency

No particular considerations are required here, since *CCY* isn't a relevant variable as I neglected FX risk in my analyses, not to introduce too much complexity. For the sake of completeness, here are the statistical quantities of Z-spread, with respect to each *CCY*:

Bond Currency vs. Z-spread (bps)

CCY	N° bonds	Z-spread Mean	Z-spread SD	Z-spread SE
AUD	16	-19.0	12.8	3.2
CAD	1	-14.9	7.4	7.4
EUR	717	45.2	92.2	3.4
GBP	6	148.4	93.9	38.4
INR	1	-29.2	10.4	10.4
JPY	1	-8.1	3.7	3.7
USD	136	42.1	78.2	6.7
ZAR	1	1.6	8.2	8.2

Table 2.3: Basic statistics: mean and standard deviation

2.3.4. ESG flag

Let us now focus on the relationship between the two key variables of my analyses: Z-spread and ESG flag (or ESG label, used as synonyms from now on).

Here is the barplot of the Z-spread Mean distribution, for each ESG class:

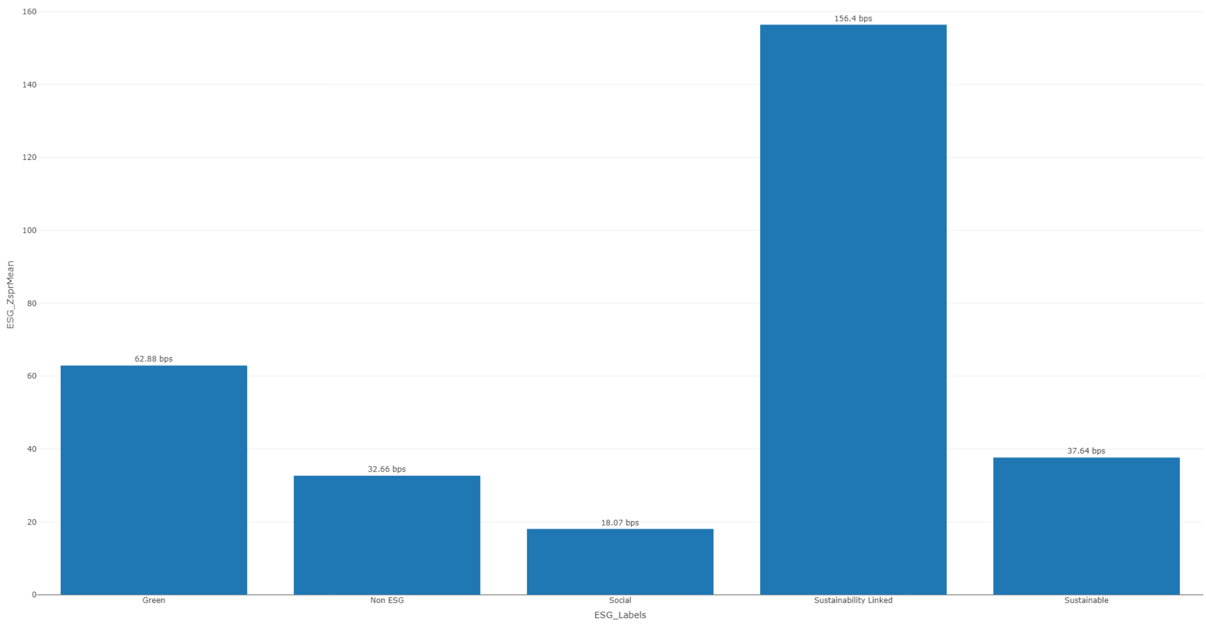


Figure 2.4: Z-spread Mean vs. ESG flag

And here are the basic statistical quantities related to the Z-spread:

ESG label vs. Z-spread (bps)

ESG label	N° bonds	Z-spread Mean	Z-spread SD	Z-spread SE
Non ESG	476	32.7	77.9	3.6
Tot. ESG	403	58.8	102.2	5.1
Green	281	62.9	100.9	6.0
Sustainable	50	37.6	97.3	13.8
Social	40	18.1	58.9	9.3
Sustain. Linked	32	156.4	140.5	24.8

Table 2.4: Basic statistics: mean and standard deviation

From the barplot and the numbers above, it can inferred that the average Z-spread of ESG bonds seems to be higher than that of conventional bonds, even with a higher standard deviation due to the smaller sub-samples sizes and heterogeneity of their composition.

This fact, which is just a guess so far and will be explored in detail later, already anticipates what will turn out to be one of the main results of this thesis.

3 | Time Series Analysis

Before commencing my quantitative analyses on the constructed database, I conducted a preliminary qualitative analysis of the time series pertaining to the variables of greatest interest. The aim of this analysis was to gain a better understanding of how these variables have evolved over time, specifically for the different types of bonds.
To achieve this, I created two dataframes from the original database; one comprising the time series data for conventional (Non ESG) bonds, and the other for ESG bonds.

The fundamental metric upon which I have founded my qualitative analysis, and subsequently the ensuing quantitative analyses, is the outstanding amount. Henceforth, only the quantities associated with non-zero outstanding amount will be deemed relevant, all rows corresponding to null outstanding amount have been eliminated.

3.1. Time Series Dataframes

The objective behind constructing these dataframes was to achieve the highest degree of balance possible, through meticulous selection of issuers such that the number of ESG bonds and non-ESG bonds were equal.

This selection then resulted in the exclusion of two unbalanced issuers, to which the bank had large exposures and therefore could have skewed the results of my future analyses:

- Kreditanstalt fuer Wiederaufbau (KFW), a German bank that issued just 12 ESG bonds compared to 57 conventional ones;
- European Union (EU), that issued 15 ESG bonds compared to 30 conventional ones.

These two issuers will be analyzed separately and with different tools, see Section 3.3 *"Unbalanced Issuers: Kreditanstalt fuer Wiederaufbau (KFW), European Union (EU)"* for more details.

Once I eliminated KFW and EU, I obtained a pool of balanced issuers whereby the two dataframes DB_TS_ESG and DB_TS_NonESG were constructed in such a way that, for each date from January 4, 2021 to November 22, 2022, it contained:

- Mean, Median, and Weighted Average, with weights corresponding to the outstanding amounts, of the Z-spreads of all those bonds to which the bank had a non-zero exposure on that date.
  These will be the key quantities on which the following qualitative analysis will rely on.

- The issuers, currencies, countries of risk, types of issue, coupon and seniority, sectors, and ratings that were the most relevant for that specific date, again using the outstanding amount as unit of comparison.
  This set of information has been gathered just to get a better understanding of the main drivers of the Z-spread changes over time, but they won't be useful for practical purposes.

As a first visualization of the results, I report here the Z-spread Mean graph for each ESG class: Non ESG, Green, Sustainable, Social and Sustainability-Linked.

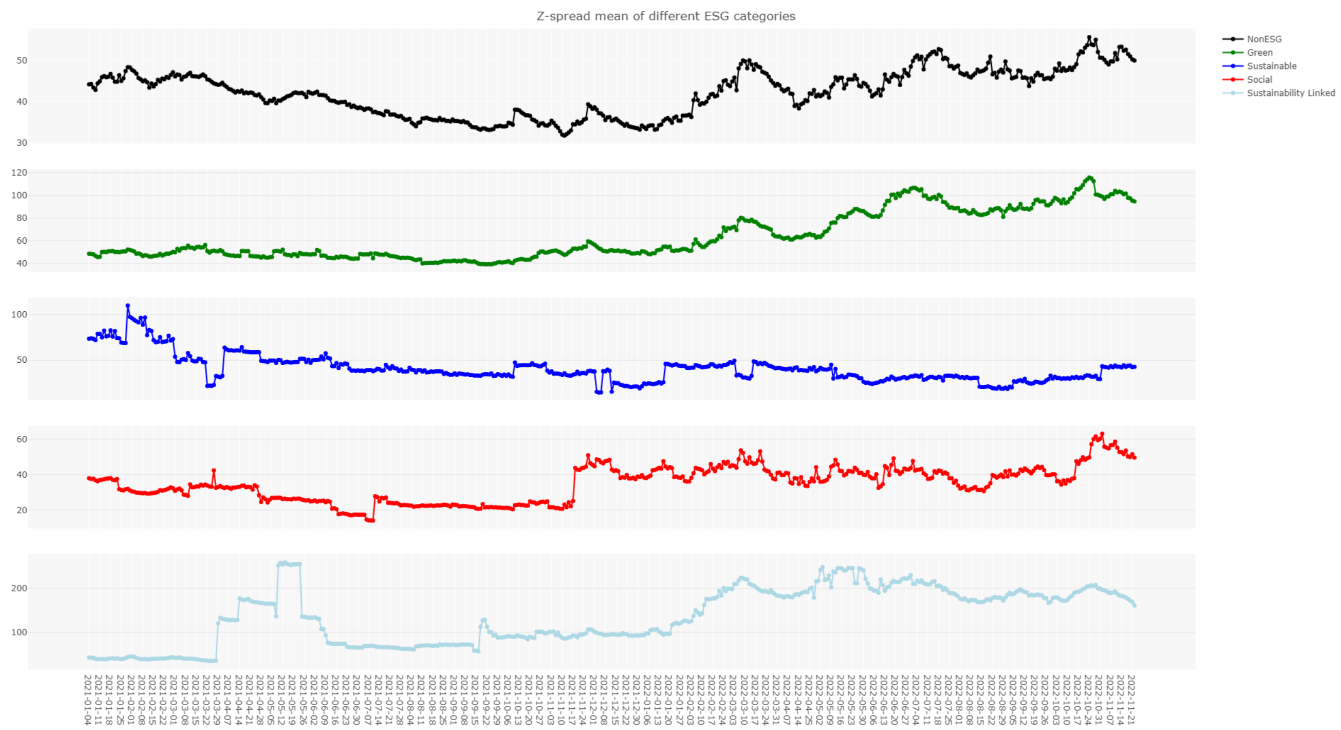


Figure 3.1: ESG Z-spread Mean Time Series

Based on an initial visual examination of the graphs, a regime shift is apparent in nearly all the time series, occurring towards the end of October 2021, which coincides with the onset of the conflict between Russia and Ukraine.

Notably, the average Z-spread witnessed an upswing for almost all ESG bond categories, owing to high levels of market uncertainty and an attendant escalation in investment risk and issuer default likelihood.

Another salient feature, which corroborates the findings of prior barplots, is that non-ESG bonds exhibit a lower average Z-spread as compared to their ESG counterparts.

3.2. Time Series Analysis

The significance of the trends identified for Z-spread Mean would be further amplified if it is also validated by the median and weighted average Z-spreads.
Consequently, the next stage of analysis entails a qualitative examination of the time series data for these two metrics.

3.2.1. Structural Breaks Detection: the Chow Test

As part of this analysis, examining the break points of the different time series is a useful exercise [34]. Indeed, detecting structural breaks can offer valuable insights into the problem at hand, since they aid us in identifying when and whether there is a significant shift in our data.

A structural break occurs when a time series abruptly changes at a specific point in time. This alteration may entail a shift in the mean or other parameters that generate the series.

The tool I used to find these breaks is the Chow test [35], a statistical test created by economist Gregory Chow and utilized to examine whether the coefficients in two regression models on separate datasets are identical.
This test is frequently utilized in econometrics with time series data to determine whether there is a structural change in the data at a certain point.

Suppose we fit the following regression model to our entire dataset:

$y_t = a + b \cdot x_{1,t} + c \cdot x_{2,t} + \epsilon$

Then suppose we split our data into two groups based on some structural break point and fit the following regression models to each group:

$y_t = a_1 + b_1 \cdot x_{1,t} + c_1 \cdot x_{2,t} + \epsilon$
$y_t = a_2 + b_2 \cdot x_{1,t} + c_2 \cdot x_{2,t} + \epsilon$

The null and alternative hypotheses of the Chow test are:

Null (H0): $a_1 = a_2$ AND $b_1 = b_2$ AND $c_1 = c_2$;
Alternative (H1): $a_1 \neq a_2$ OR $b_1 \neq b_2$ OR $c_1 \neq c_2$.

In the event that we reject the null hypothesis, it can be concluded that there exists a structural break point in the data, because two regression lines could provide a better fit than a single one and so there are two different underlying structures for our data.
On the other hand, if the null hypothesis is not rejected, it cannot be concluded that there exists a structural break point in the data. This implies that the regression lines can be "pooled" into one single regression line that accurately represents the data pattern.

The Chow test statistic is computed as follows:

$S = \frac{[RSS_{Tot} - (RSS_1 + RSS_2)]/k}{(RSS_1 + RSS_2)/(N_1 + N_2 - 2 \cdot k)}$, where:

- RSS_{Tot} is the sum of squared residuals [1] from the total data;
- RSS_1, RSS_2 are the sum of squared residuals, for each sub-sample of data;
- N_1, N_2 are the number of observations, for each sub-sample of data;
- k is the number of parameters of the model.

[1]The residual sum of squares (RSS) is a statistical measure that represents the sum of the squared differences between the observed values and the predicted values of a regression model.
In other words, RSS measures the amount of variability in the dependent variable that is not explained by the independent variables included in the model.
It is commonly used in regression analysis to assess the goodness of fit of a model and to compare the performance of different regression models. A smaller RSS value indicates a better fit of the model to the data.

It is computed with this formula:

$RSS = \sum_{i=1}^{N} [y_i - f(x_i)]^2$, where:

- y_i is the i-th value of the variable to be predicted;
- $f(x_i)$ is the predicted value of y_i, through the model function f and starting from input x_i;
- N is the number of input variables at disposal.

In the event that the p-value associated with the test statistic is lower than a specified level of significance (I consider 5% as upper threshold), it is possible to reject the null hypothesis and deduce that there exists a structural break point in the data.

3.2.2. ESG vs Non ESG Graphical Comparison

At this point, we are ready to study Z-spread time series in detail: ESG and Non ESG time series will be analyzed separately, with a special focus on Z-spread Median and Weighted Average that will be the two most relevant variables.

Z-spread Median and Weighted Average: Time Series Decomposition and Structural Breaks

Below are the graphs of the Median and the Weighted Average time series, for both ESG and Non ESG dataframes. Moreover, they include their respective decomposed time series into three different terms: trend, seasonality and noise (or residual). Lastly, there is the additional information about their break points, identified thanks to Chow tests described above and indicated by a dashed red line.

To begin, let's conduct a graphical inspection of the ESG bond time series.

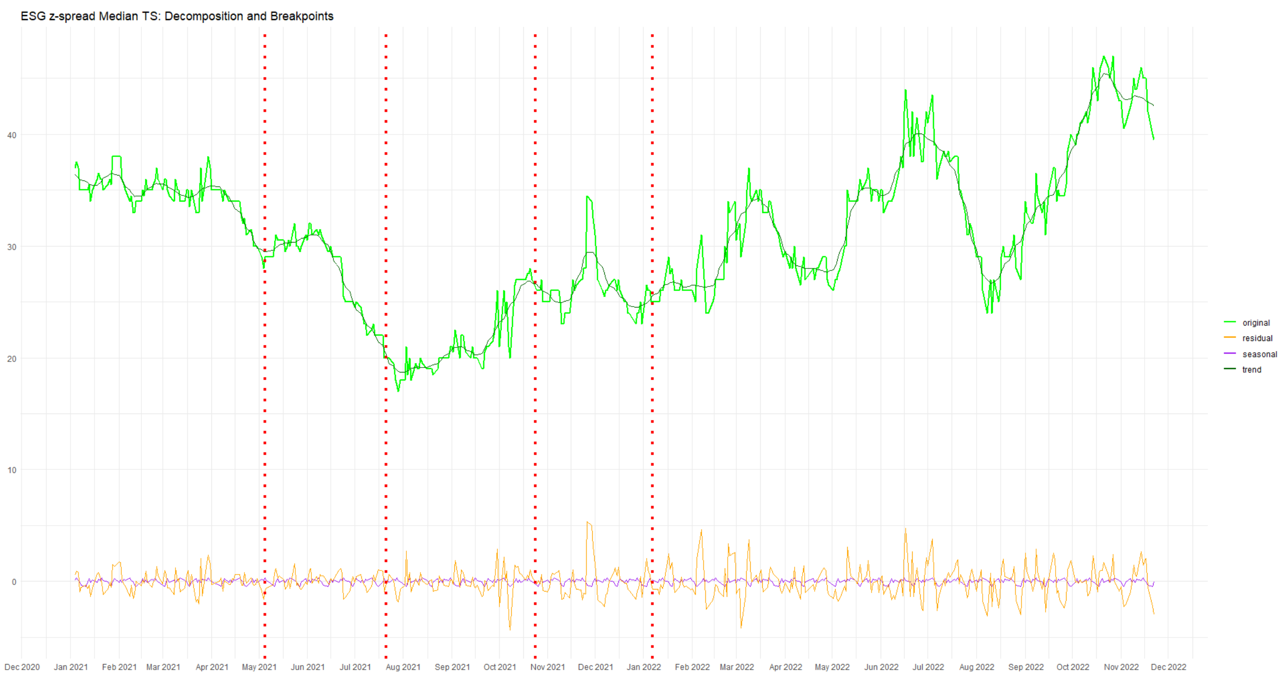


Figure 3.2: ESG Z-spread Median TS: Decomposition and Breakpoints

The median value of the Z-spread of ESG bonds remained steady at around 35 basis points in the first part of 2021 before dropping by approximately 10 basis points in the period leading up to the conflict between Russia and Ukraine. The historical series features four break points that are concentrated within a timeframe of approximately eight months. Following the outbreak of war, the series began to return to its pre-war levels, although there were large fluctuations accompanied by a much more pronounced noise component. This trend began in February 2022 and ends up to a final level of around 45 bps.

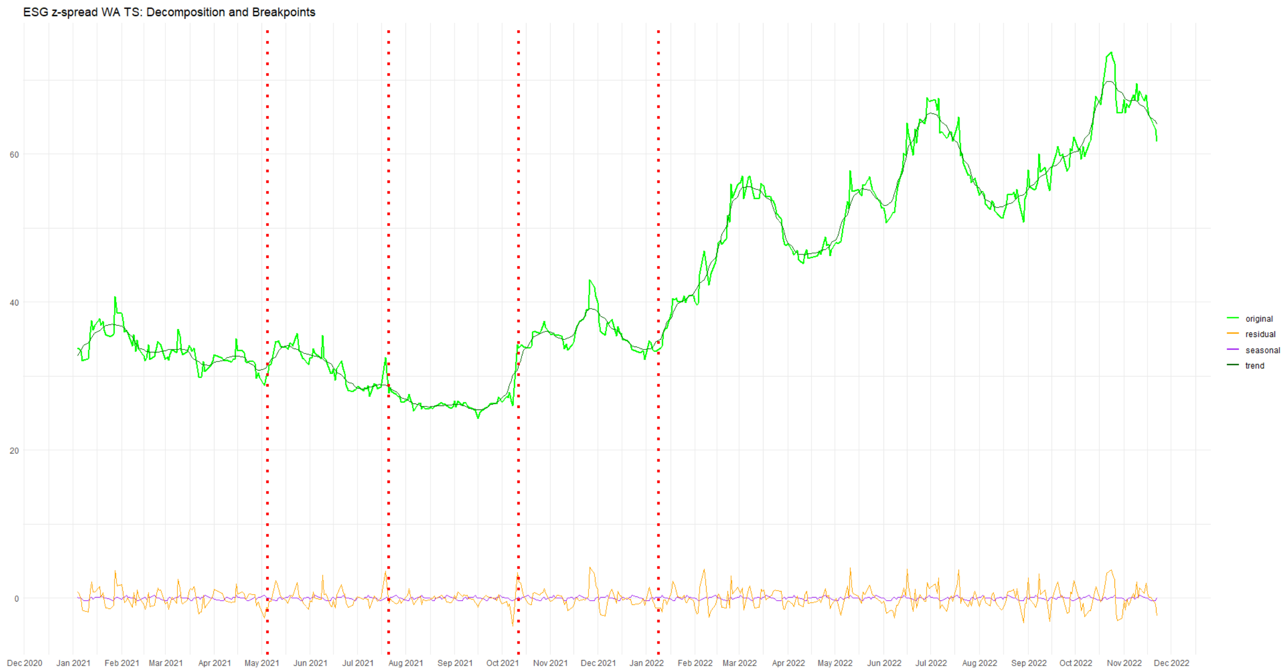


Figure 3.3: ESG z-spread Weighted Average TS: Decomposition and Breakpoints

The Z-spread weighted average of ESG bonds exhibits comparable trends and values to the previously analyzed median, but with less pronounced fluctuations and a smaller noise component. The overall trend remains relatively stable in the period leading up to the conflict outbreak, with the four break points previously identified for the median confirmed at similar dates. Following this period, there is a shift to an upward trend that eventually settles around a Z-spread value of 60 basis points toward the end of 2022.

The same two graphs are also reproduced for Non ESG bonds:

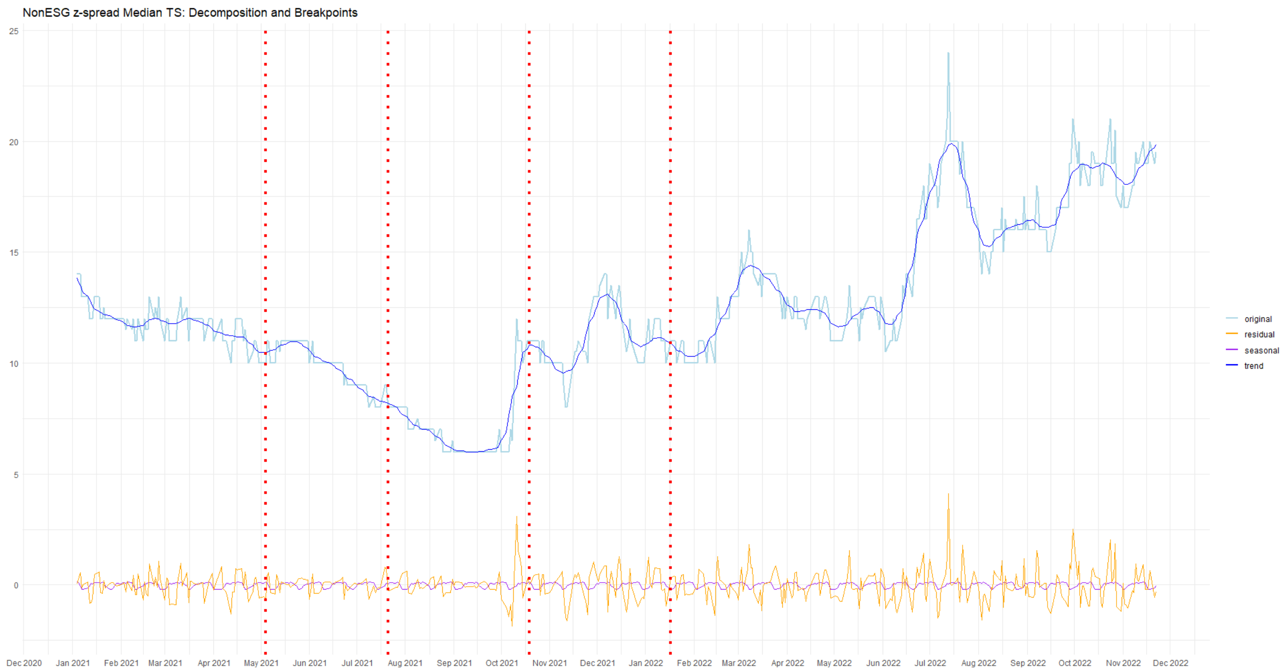


Figure 3.4: Non ESG z-spread Median TS: Decomposition and Breakpoints

Upon initial observation, the historical series of Non-ESG bonds appears to have significantly lower values compared to the corresponding ESG bonds, with a difference of approximately 20 basis points between the two. Despite this difference, the break points in the Non-ESG series are located at similar dates to those in the ESG series, and the trend of the median Non-ESG series is also similar to that previously described for ESG bonds.

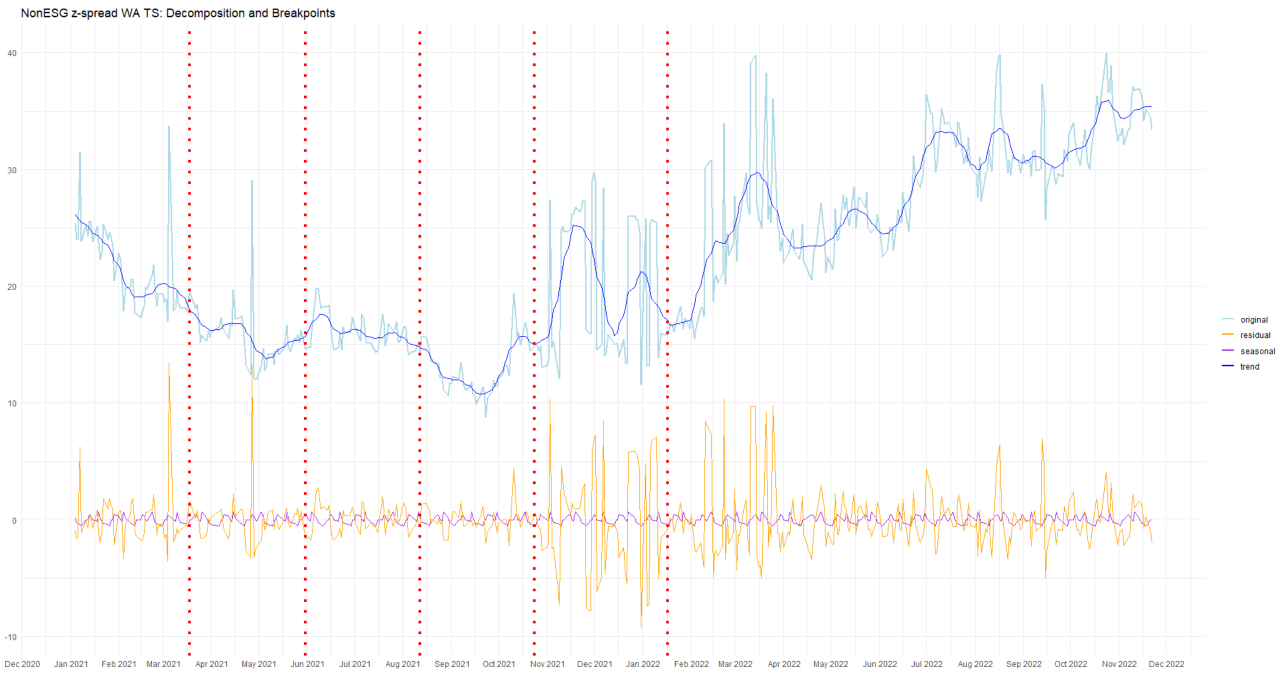


Figure 3.5: Non ESG z-spread Weighted Average TS: Decomposition and Breakpoints

Upon analyzing the graph of the weighted average of Non ESG bonds, it becomes apparent that the series is significantly noisier than the others.
This additional noise is likely the cause of the extra break point observed between March and April 2021; in fact, even a superficial visual inspection of the graph shows that at that point there is no substantial change in any of the three components that make up the time series. Moreover, the lack of presence of the additional break point in the Median time series of the Non-ESG bonds' Z-spread further reduces its credibility.

Despite this noise, the trend of the Non ESG series appears similar to those previously discussed as ESG bonds keep having higher Z-spreads on average than conventional ones. However, it is worth noticing that this Weighted Average time series appears to enlarge the Z-spread delta between ESG and Non-ESG bonds, as it lies in the range of about 12 to 36 bps and it is thus higher than the Median delta, which is contained in the range of about 7 to 20 bps instead.

To conclude, here is a table in which the dates corresponding to the break points in the graphs above are collected:

Structural Break Dates

Dates	ESG Median	Non ESG Median	ESG W.A.	Non ESG W.A.
1st	-	-	-	2021-03-18
2nd	2021-05-05	2021-05-04	2021-05-05	2021-05-31
3rd	2021-07-21	2021-07-21	2021-07-21	2021-08-12
4th	2021-10-24	2021-10-19	2021-10-12	2021-10-24
5th	2022-01-07	2022-01-17	2022-01-09	2022-01-17

Table 3.1: Structural Break Dates for ESG and Non ESG Time Series.

To summarize, this graphical analysis indicates that the time series describing the Z-spread of ESG and Non-ESG bonds appear to exhibit comparable structural breaks, indicating that they react in a similar manner to external stimuli, after accounting for exogenous noise. This observation is crucial, as it allows for quantitative analysis of these bonds on an equal footing, without the need for special assumptions to put them on the same level.

Furthermore, the analysis reveals a systematic difference between the Z-spreads of ESG and Non-ESG bonds. Specifically, it appears that ESG bonds have a higher average Z-spread than their conventional bond counterparts.
This finding is significant, as it partially addresses the research question of this thesis. With higher Z-spreads, ESG bonds are considered riskier and, consequently, have a lower value than conventional bonds. As a result, they may be more attractive to some investors at a first glance, as they offer an alternative risk profile, i.e. lower cost for the same characteristics, in exchange for a higher risk.

Given the centrality of this theme for my research, it is crucial to further explore this trend by comparing the time series of Z-spreads and to see how any differences are reflected in the price of those bonds.

Focus on Z-spread Time Series: Impact On Prices

As mentioned above, it is worth deepening the investigation about the Z-spread difference that appeared between ESG and conventional bonds. After doing so, for the sake of completeness, I will analyze how any difference would reflect in the prices of such bonds.

Let's start visualizing the Z-spread time series:

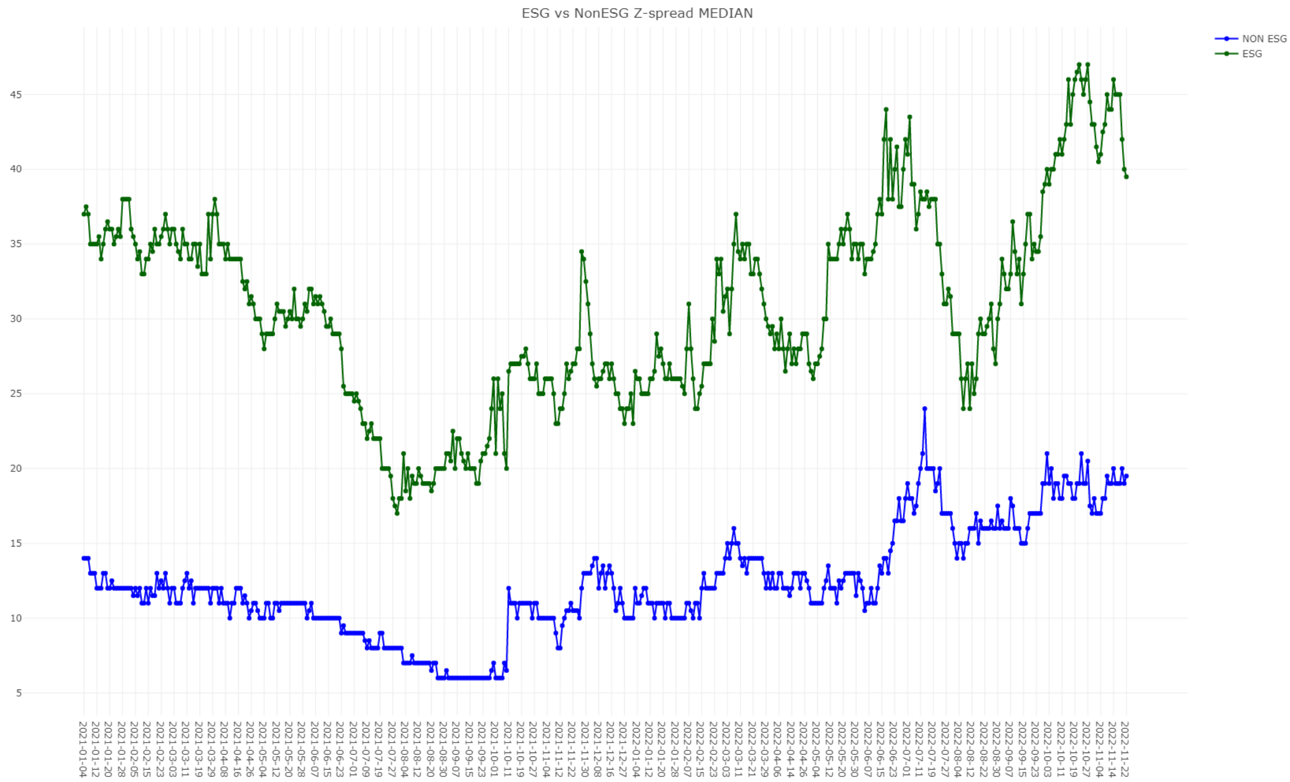


Figure 3.6: ESG vs NonESG: Median Comparison

As can be seen from this graph, which contains the time series of ESG and Non-ESG bonds' Z-spreads Median, there is a systematic difference between the two, ranging from a minimum of 8 bps to a maximum of 25 bps.

The same trend can be witnessed in the graph of the time series of ESG and Non-ESG bonds' Z-spreads Weighted Average, with Z-spreads' weights given by the outstanding amounts of the corresponding bonds.

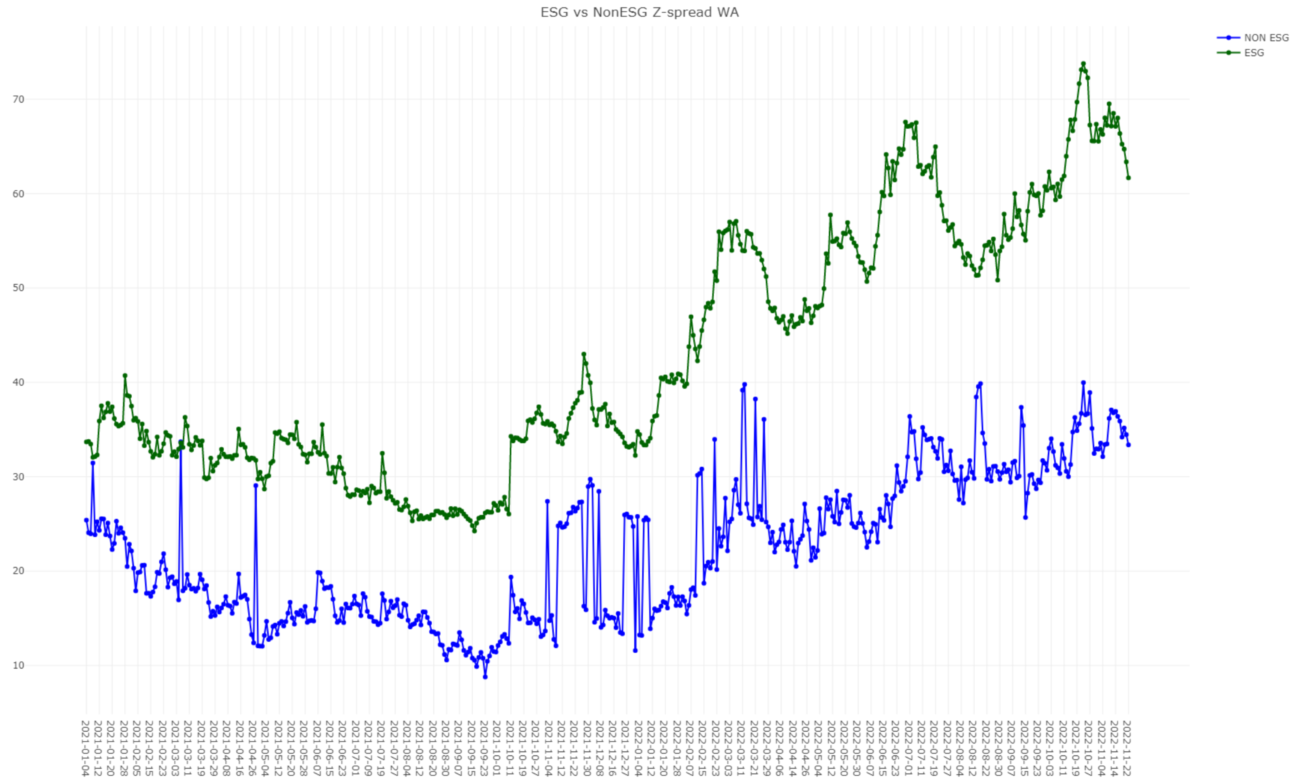


Figure 3.7: ESG vs NonESG: Weighted Average Comparison

As indicated by the Weighted Average chart, which has been adjusted for the same noise previously associated to non-ESG bonds, the Z-spread difference is substantiated. The only remaining question is whether this differential is reflected, as one would expect, in a favorable price differential for ESG bonds.

To this end, let's visualize the time series of the Mean, the Median and the Weighted Average (as usual, with weights equal to the outstanding amounts) of the bonds' prices:

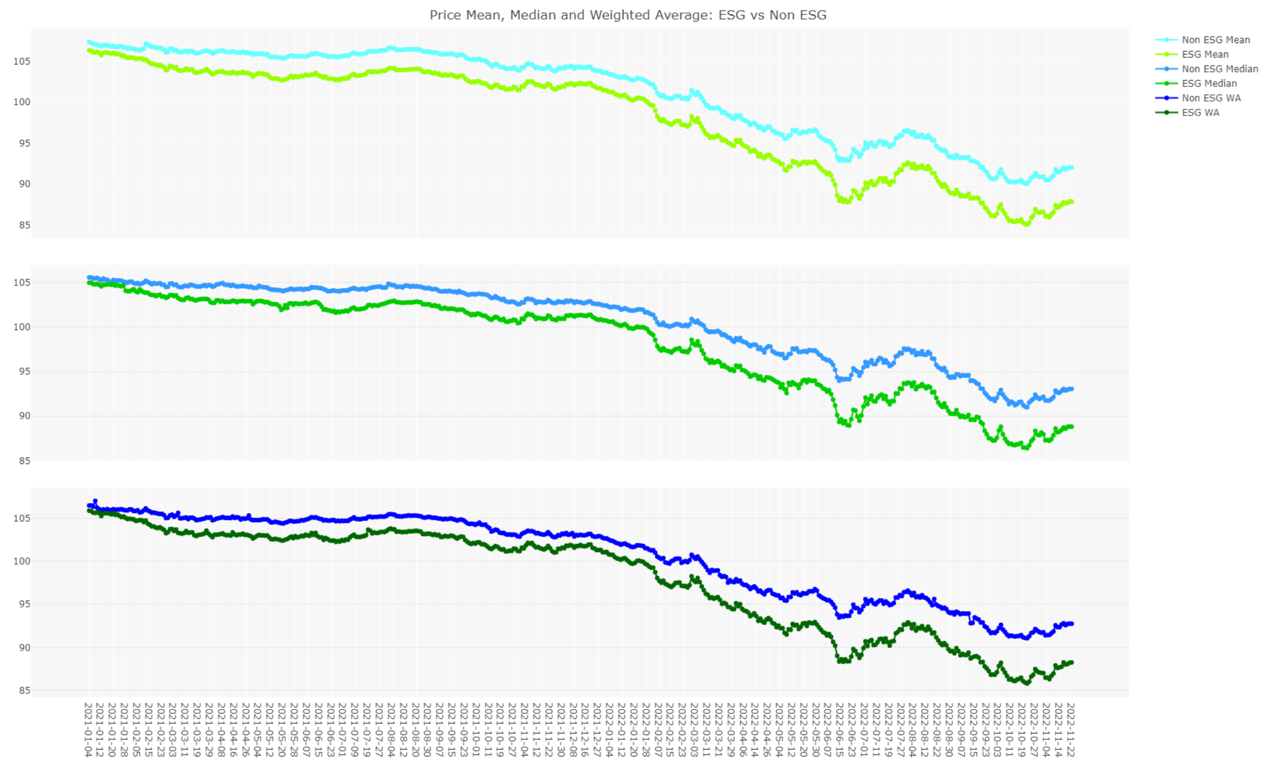


Figure 3.8: Price Mean, Median and Weighted Average: ESG vs Non ESG

From this latest graph, a very clear and uniform trend can be seen on all the three different measures chosen to display prices trends: ESG bonds' value is systematically less than conventional ones. The difference is very subtle at the beginning of 2021, but then widens more and more as time goes on.

These findings complete the answer of my thesis's initial research question, since they indicate the existence of an ESG Premium in the corporate bond market. ESG bonds are priced lower than their conventional peers, making them an attractive option for investors upon initial examination.

The primary objective of my subsequent analyses is thus to examine the reasons for these disparities. To achieve this, I will employ a simple logistic regression model as a preliminary step, followed by the use of more complex and advanced mathematical tools such as Neural Networks.

3.3. Unbalanced Issuers: Kreditanstalt fuer Wiederaufbau (KFW), European Union (EU)

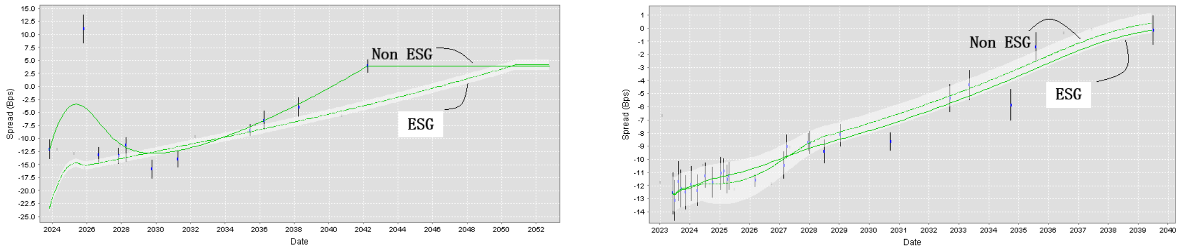
Prior to employing the quantitative methods mentioned earlier, I conduct a separate analysis of the two unbalanced issuers, Kreditanstalt fuer Wiederaufbau (KFW) and European Union (EU), using Z-spread curves generated by the tools provided by the bank.

I recall that both of these issuers were excluded from the database to which quantitative methods are applied, due to the disparity between the numbers of ESG and conventional bonds issued by them and possessed by the bank. This discrepancy could potentially introduce a bias into the results of my analyses, particularly given the high exposures the bank had on them, as well as the significant outstanding amounts of these bonds.

Such curves are created through the interpolation of various Z-spread points, one for each single bond and corresponding to the bonds' maturities.
The curves are composed of two levels: the first one is constructed by means of conventional bonds (L1), while the second one is constructed by interpolating ESG bonds' Z-spreads (L2). The difference between the two levels determines the ESG Z-spread Premium, that can be either positive or negative, in principle.

As the Z-spreads of the bonds that make up the curve change over time, the curve also evolves accordingly. This enables us to track the Z-spread delta between ESG and non-ESG bonds throughout the relevant period, thereby providing insight into the changes or risk perceptions associated with these bonds.

I show below a couple of snapshots of the two curves, at a certain date, just to make the procedure adopted more understandable.



(a) EU Curve. (b) KFW Curve.

Figure 3.9: European Union (EU) and Kreditanstalt fuer Wiederaufbau (KFW): Z-spread curve construction.

Of particular interest is the variation in Z-spread delta observed between the period spanning from January 2021 to November 2022, with a particular focus on the transition between the period straddling the outbreak of the Russian-Ukraine conflict.

To assess this, I gathered monthly curve levels on target dates (EoM) and calculated the delta between the two curves.

The resulting values collected are as follows:

2021	Jan-21			Feb-21			Mar-21			Apr-21			May-21			Jun-21		
	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta
3M	-12.76	-24.04	-11.28	-11.41	-19.14	-7.74	-11.14	-19.57	-8.43	-11.56	-20.04	-8.48	-9.33	-17.24	-7.91	-9.88	-17.56	-7.67
6M	-12.76	-24.04	-11.28	-11.41	-19.14	-7.74	-11.14	-19.57	-8.43	-11.56	-20.04	-8.48	-9.33	-17.24	-7.91	-9.88	-17.56	-7.67
1Y	-12.76	-24.04	-11.28	-11.41	-19.14	-7.74	-11.14	-19.57	-8.43	-11.56	-20.04	-8.48	-9.33	-17.24	-7.91	-9.88	-17.56	-7.67
2Y	-12.76	-24.04	-11.28	-11.41	-19.14	-7.74	-11.14	-19.57	-8.43	-11.56	-20.04	-8.48	-9.33	-17.24	-7.91	-9.88	-17.56	-7.67
3Y	-10.03	-21.31	-11.28	-7.87	-15.61	-7.74	-6.86	-15.29	-8.43	-6.69	-15.16	-8.48	-3.54	-11.45	-7.91	-3.42	-11.09	-7.67
4Y	-3.88	-15.16	-11.28	-2.10	-9.84	-7.74	-1.88	-10.31	-8.43	-2.40	-10.87	-8.48	1.06	-6.85	-7.91	-0.13	-7.80	-7.67
5Y	-4.96	-15.30	-10.33	-3.03	-9.57	-6.53	-3.04	-10.15	-7.11	-3.77	-10.70	-6.93	0.50	-5.92	-6.42	-2.54	-8.79	-6.25
6Y	-9.13	-14.53	-5.39	-6.57	-8.47	-1.90	-6.24	-9.92	-3.68	-6.74	-10.18	-3.44	-1.40	-5.03	-3.63	-4.44	-7.62	-3.18
7Y	-12.35	-13.96	-1.61	-9.06	-7.58	1.48	-8.18	-9.76	-1.58	-8.42	-9.74	-1.32	-2.14	-4.26	-2.12	-4.45	-6.53	-2.07
8Y	-13.74	-13.48	0.26	-9.90	-6.82	3.09	-8.40	-9.56	-1.16	-8.56	-9.33	-0.77	-1.60	-3.47	-1.87	-3.54	-5.42	-1.88
9Y	-14.00	-13.03	0.97	-9.77	-6.12	3.66	-7.59	-9.31	-1.72	-7.82	-8.91	-1.09	-0.39	-2.65	-2.26	-2.13	-4.27	-2.14
10Y	-13.66	-12.56	1.10	-9.16	-5.45	3.71	-6.30	-9.00	-2.70	-6.72	-8.49	-1.77	1.06	-1.79	-2.85	-0.45	-3.10	-2.65
12Y	-12.04	-11.54	0.50	-7.28	-4.17	3.11	-3.64	-8.22	-4.58	-4.67	-7.61	-2.95	3.61	-0.01	-3.62	2.89	-0.84	-3.73
15Y	-8.36	-9.74	-1.39	-3.90	-2.32	1.57	-1.95	-6.71	-4.76	-4.39	-6.20	-1.82	4.47	2.72	-1.75	5.68	2.25	-3.43
20Y	-0.13	-6.13	-6.00	3.35	0.75	-2.60	3.57	-3.52	-7.10	1.82	-3.51	-5.33	12.07	7.42	-4.65	11.06	6.96	-4.10
25Y	2.23	-1.87	-4.10	5.27	4.06	-1.22	5.23	0.07	-5.17	3.24	-0.09	-3.33	13.17	12.53	-0.64	15.23	12.24	-3.00
30Y	2.23	2.69	0.46	5.27	7.57	2.30	5.23	2.86	-2.38	3.24	3.73	0.49	13.17	15.66	2.49	18.02	16.21	-1.82

2021	Jul-21			Aug-21			Sep-21			Oct-21			Nov-21			Dec-21		
	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta
3M	-12.60	-24.16	-11.56	-13.54	-24.89	-11.35	-13.32	-23.31	-10.00	-16.00	-27.31	-11.31	-20.86	-35.25	-14.39	-23.15	-35.82	-12.67
6M	-12.60	-24.16	-11.56	-13.54	-24.89	-11.35	-13.32	-23.31	-10.00	-16.00	-27.31	-11.31	-20.86	-35.25	-14.39	-23.15	-35.82	-12.67
1Y	-12.60	-24.16	-11.56	-13.54	-24.89	-11.35	-13.32	-23.31	-10.00	-16.00	-27.31	-11.31	-20.86	-35.25	-14.39	-23.15	-35.82	-12.67
2Y	-12.60	-24.16	-11.56	-13.54	-24.89	-11.35	-13.32	-23.31	-10.00	-16.00	-27.31	-11.31	-19.92	-34.31	-14.39	-21.24	-33.91	-12.67
3Y	-5.46	-17.02	-11.56	-5.80	-17.14	-11.35	-5.62	-15.62	-10.00	-8.33	-19.63	-11.31	-12.34	-26.73	-14.39	-14.52	-27.19	-12.67
4Y	-3.65	-15.21	-11.56	-4.18	-15.53	-11.35	-4.97	-14.97	-10.00	-8.27	-19.58	-11.31	-13.44	-27.47	-14.03	-15.75	-27.75	-11.99
5Y	-6.84	-14.55	-7.71	-7.23	-14.54	-7.31	-8.37	-14.45	-6.08	-11.28	-18.05	-6.77	-16.68	-25.00	-8.32	-18.61	-25.46	-6.84
6Y	-8.61	-13.02	-4.42	-8.96	-12.96	-4.00	-10.26	-13.41	-3.15	-12.57	-16.52	-3.95	-17.17	-22.48	-5.31	-18.89	-23.10	-4.21
7Y	-8.90	-11.71	-2.81	-9.30	-11.57	-2.27	-10.76	-12.43	-1.67	-12.72	-15.12	-2.41	-16.40	-20.23	-3.83	-18.16	-21.02	-2.87
8Y	-8.58	-10.52	-1.94	-9.05	-10.28	-1.23	-10.40	-11.48	-1.08	-12.21	-13.82	-1.61	-15.11	-18.28	-3.16	-17.01	-19.25	-2.23
9Y	-7.66	-9.38	-1.73	-8.27	-9.03	-0.76	-9.09	-10.53	-1.44	-10.95	-12.58	-1.63	-13.32	-16.57	-3.25	-15.06	-17.73	-2.67
10Y	-6.05	-8.28	-2.23	-6.88	-7.81	-0.93	-7.04	-9.58	-2.54	-9.08	-11.38	-2.30	-11.15	-15.05	-3.90	-12.22	-16.42	-4.20
12Y	-1.77	-6.14	-4.37	-3.07	-5.46	-2.38	-2.76	-7.68	-4.92	-5.09	-9.12	-4.03	-7.01	-12.46	-5.45	-6.09	-14.27	-8.18
15Y	1.69	-3.16	-4.85	1.11	-2.22	-3.33	-0.37	-4.95	-4.58	-2.15	-6.01	-3.86	-4.01	-9.19	-5.18	-3.05	-11.64	-8.59
20Y	4.51	1.22	-3.28	5.55	2.51	-3.04	2.82	-0.77	-3.59	2.01	-0.70	-2.71	0.14	-3.16	-3.31	-0.46	-6.02	-5.56
25Y	8.25	5.68	-2.56	10.84	7.53	-3.31	7.36	3.78	-3.58	8.24	5.81	-2.43	7.23	4.80	-2.43	5.31	1.85	-3.46
30Y	9.93	9.31	-0.62	14.77	12.69	-2.07	10.37	8.29	-2.08	14.67	12.75	-1.92	14.07	12.95	-1.13	10.51	9.07	-1.45

2022	Jan-22			Feb-22			Mar-22			Apr-22			May-22			Jun-22		
	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta
3M	-23.26	-33.52	-10.26	-24.59	-34.66	-10.08	-28.42	-36.97	-8.54	-34.54	-45.27	-10.73	-37.33	-47.02	-9.68	-35.02	-45.08	-10.06
6M	-23.26	-33.52	-10.26	-24.59	-34.66	-10.08	-28.42	-36.97	-8.54	-34.54	-45.27	-10.73	-37.33	-47.02	-9.68	-35.02	-45.08	-10.06
1Y	-23.26	-33.52	-10.26	-24.59	-34.66	-10.08	-28.42	-36.97	-8.54	-34.54	-45.27	-10.73	-37.33	-47.02	-9.68	-35.02	-45.08	-10.06
2Y	-20.43	-30.69	-10.26	-21.90	-31.98	-10.08	-24.84	-33.38	-8.54	-29.43	-40.16	-10.73	-35.18	-44.86	-9.68	-32.08	-42.14	-10.06
3Y	-13.95	-24.20	-10.26	-17.94	-28.02	-10.08	-20.40	-28.94	-8.54	-24.23	-34.96	-10.73	-27.39	-37.07	-9.68	-24.04	-34.10	-10.06
4Y	-14.66	-23.75	-9.09	-19.09	-27.68	-8.60	-20.65	-27.08	-6.44	-24.19	-31.60	-7.41	-24.01	-30.40	-6.39	-20.58	-26.36	-5.78
5Y	-16.83	-20.95	-4.12	-20.03	-24.76	-4.74	-20.62	-23.08	-2.46	-23.99	-27.53	-3.54	-23.39	-25.83	-2.45	-19.71	-22.05	-2.34
6Y	-16.56	-18.39	-1.83	-18.74	-22.10	-3.36	-18.55	-19.86	-1.31	-22.23	-24.56	-2.33	-21.39	-22.49	-1.10	-17.88	-19.16	-1.29
7Y	-14.96	-16.18	-1.21	-16.63	-19.79	-3.16	-15.89	-17.35	-1.46	-20.22	-22.34	-2.13	-18.53	-19.88	-1.36	-15.58	-17.05	-1.47
8Y	-12.70	-14.27	-1.57	-14.29	-17.79	-3.51	-13.31	-15.34	-2.03	-18.32	-20.62	-2.30	-15.47	-17.76	-2.29	-13.38	-15.40	-2.01
9Y	-9.94	-12.61	-2.67	-11.83	-16.04	-4.21	-10.86	-13.66	-2.80	-16.36	-19.24	-2.88	-12.47	-15.98	-3.51	-11.39	-14.04	-2.65
10Y	-7.04	-11.11	-4.07	-9.35	-14.48	-5.13	-8.50	-12.19	-3.69	-14.15	-18.11	-3.96	-9.74	-14.44	-4.71	-9.51	-12.87	-3.35
12Y	-2.69	-8.50	-5.81	-5.11	-11.78	-6.67	-4.70	-9.59	-4.89	-9.84	-16.35	-6.50	-6.39	-11.95	-5.56	-6.65	-10.72	-4.07
15Y	-1.68	-5.14	-3.46	-3.14	-8.35	-5.20	-2.47	-5.81	-3.33	-7.40	-14.05	-6.65	-4.64	-8.70	-4.06	-2.76	-6.40	-3.64
20Y	1.96	0.90	-1.05	1.47	-2.12	-3.59	4.76	1.86	-2.90	-0.22	-7.02	-6.80	4.46	0.39	-4.07	7.98	6.05	-1.93
25Y	9.60	8.79	-0.81	7.97	6.10	-1.87	12.30	11.08	-1.22	7.28	3.03	-4.26	15.12	12.57	-2.55	19.63	19.44	-0.19
30Y	17.43	16.66	-0.77	13.47	14.46	0.99	18.85	20.97	2.12	12.77	13.22	0.45	25.72	24.77	-0.95	32.16	33.34	1.18

2022	Jul-22			Aug-22			Sep-22			Oct-22			Nov-22			Dec-22		
	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta
3M	-38.38	-47.94	-9.57	-42.13	-51.68	-9.55	-48.69	-59.19	-10.50	-50.89	-60.20	-9.31	-46.46	-55.88	-9.42	-48.05	-61.73	-13.68
6M	-38.38	-47.94	-9.57	-42.13	-51.68	-9.55	-48.69	-59.19	-10.50	-50.89	-60.20	-9.31	-46.46	-55.88	-9.42	-48.05	-61.73	-13.68
1Y	-38.38	-47.94	-9.57	-42.13	-51.68	-9.55	-48.69	-59.19	-10.50	-50.89	-60.20	-9.31	-45.90	-55.32	-9.42	-46.54	-60.22	-13.68
2Y	-34.86	-44.42	-9.57	-36.48	-46.02	-9.55	-43.36	-53.86	-10.50	-41.35	-50.66	-9.31	-35.32	-44.74	-9.42	-33.20	-46.88	-13.68
3Y	-26.02	-35.59	-9.57	-26.87	-36.41	-9.55	-32.10	-42.60	-10.50	-30.45	-39.76	-9.31	-24.49	-33.27	-8.78	-21.24	-33.64	-12.40
4Y	-22.95	-27.78	-4.83	-23.25	-28.72	-5.47	-27.45	-32.94	-5.50	-23.93	-30.62	-6.69	-19.98	-24.97	-5.00	-16.82	-24.23	-7.41
5Y	-22.55	-23.49	-0.93	-21.82	-24.26	-2.44	-25.84	-27.83	-1.99	-20.40	-25.17	-4.78	-17.72	-19.56	-1.84	-14.04	-17.91	-3.87
6Y	-20.92	-20.60	0.32	-19.48	-21.01	-1.53	-23.47	-24.13	-0.66	-17.06	-20.95	-3.89	-14.71	-15.35	-0.64	-10.53	-13.14	-2.61
7Y	-18.53	-18.48	0.05	-16.56	-18.47	-1.91	-20.67	-21.17	-0.51	-13.59	-17.40	-3.81	-11.35	-11.85	-0.50	-6.97	-9.25	-2.27
8Y	-16.12	-16.80	-0.68	-13.68	-16.37	-2.69	-17.75	-18.61	-0.86	-10.52	-14.24	-3.72	-8.42	-8.75	-0.33	-4.09	-5.81	-1.72
9Y	-13.97	-15.38	-1.41	-11.16	-14.56	-3.40	-14.85	-16.28	-1.43	-8.08	-11.28	-3.20	-6.13	-5.85	0.28	-2.04	-2.61	-0.56
10Y	-12.05	-14.10	-2.05	-9.09	-12.93	-3.84	-12.16	-14.05	-1.89	-6.18	-8.39	-2.21	-4.29	-3.05	1.25	-0.58	0.52	1.10
12Y	-9.21	-11.65	-2.43	-6.42	-9.93	-3.51	-8.26	-9.61	-1.35	-3.01	-2.40	0.60	-0.81	2.71	3.52	2.47	6.81	4.34
15Y	-4.37	-6.79	-2.42	-1.24	-4.54	-3.30	-1.88	-1.43	0.45	6.91	8.52	1.61	9.11	12.87	3.76	13.37	16.75	3.38
20Y	6.09	5.48	-0.62	11.00	8.22	-2.78	15.02	15.96	0.94	30.05	29.07	-0.98	30.40	31.17	0.77	33.60	32.61	-0.99
25Y	15.58	16.51	0.93	22.22	19.69	-2.53	29.59	30.08	0.49	47.24	44.84	-2.40	45.42	45.47	0.05	48.11	46.04	-2.07
30Y	26.75	28.58	1.84	34.31	35.86	1.55	40.06	50.25	10.18	56.49	62.12	5.63	53.36	61.34	7.98	58.31	61.67	3.36

Figure 3.10: European Union Z-spreads: ESG vs Non ESG

2021	Jan-21			Feb-21			Mar-21			Apr-21		
	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta
3M	-13.06	-13.89	-0.82	-12.11	-12.70	-0.59	-11.30	-12.76	-1.46	-11.41	-12.48	-1.07
6M	-13.06	-13.89	-0.82	-12.11	-12.70	-0.59	-11.30	-12.76	-1.46	-11.41	-12.48	-1.07
1Y	-13.06	-13.89	-0.82	-12.11	-12.70	-0.59	-11.30	-12.76	-1.46	-11.41	-12.48	-1.07
2Y	-13.06	-13.89	-0.82	-12.11	-12.70	-0.59	-11.30	-12.76	-1.46	-11.41	-12.48	-1.07
3Y	-12.14	-12.97	-0.82	-10.15	-10.73	-0.59	-9.85	-11.31	-1.46	-10.10	-11.17	-1.07
4Y	-11.08	-12.13	-1.05	-8.51	-9.55	-1.04	-8.31	-10.13	-1.82	-8.91	-10.64	-1.73
5Y	-10.48	-11.33	-0.85	-7.46	-8.41	-0.94	-7.32	-8.82	-1.50	-8.27	-9.88	-1.61
6Y	-9.82	-10.13	-0.31	-6.36	-6.64	-0.28	-6.39	-7.05	-0.66	-7.70	-8.75	-1.06
7Y	-9.39	-9.11	0.28	-5.69	-5.24	0.45	-5.91	-5.85	0.05	-7.38	-8.04	-0.66
8Y	-9.37	-9.03	0.34	-5.62	-5.19	0.42	-5.97	-5.91	0.05	-7.39	-8.50	-1.11
9Y	-9.42	-9.08	0.34	-5.71	-5.28	0.42	-6.16	-6.11	0.05	-7.49	-8.77	-1.28
10Y	-9.22	-8.88	0.34	-5.62	-5.20	0.42	-6.16	-6.11	0.05	-7.45	-8.73	-1.28
12Y	-7.82	-7.48	0.34	-4.64	-4.21	0.42	-5.21	-5.16	0.05	-6.63	-7.91	-1.28
15Y	-4.76	-4.42	0.34	-2.47	-2.05	0.42	-3.06	-3.01	0.05	-4.77	-6.06	-1.28
20Y	-3.19	-2.85	0.34	-2.03	-1.61	0.42	-2.69	-2.63	0.05	-4.69	-5.98	-1.28
25Y	-3.19	-2.85	0.34	-2.03	-1.61	0.42	-2.69	-2.63	0.05	-4.69	-5.98	-1.28
30Y	-3.19	-2.85	0.34	-2.03	-1.61	0.42	-2.69	-2.63	0.05	-4.69	-5.98	-1.28

2021	May-21			Jun-21			Jul-21			Aug-21		
	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta
3M	-10.22	-11.57	-1.35	-10.19	-10.94	-0.75	-12.40	-12.50	-0.10	-12.30	-13.00	-0.70
6M	-10.22	-11.57	-1.35	-10.19	-10.94	-0.75	-12.40	-12.50	-0.10	-12.30	-13.00	-0.70
1Y	-10.22	-11.57	-1.35	-10.19	-10.94	-0.75	-12.40	-12.50	-0.10	-12.30	-13.00	-0.70
2Y	-10.22	-11.57	-1.35	-10.33	-11.08	-0.75	-12.77	-12.87	-0.10	-13.09	-13.78	-0.70
3Y	-8.62	-9.97	-1.35	-9.39	-10.29	-0.90	-13.30	-13.46	-0.16	-13.84	-14.51	-0.67
4Y	-6.88	-8.91	-2.03	-7.94	-9.62	-1.68	-12.85	-13.23	-0.37	-13.36	-13.95	-0.59
5Y	-5.56	-7.17	-1.61	-6.99	-8.23	-1.24	-12.28	-12.61	-0.33	-12.66	-13.10	-0.44
6Y	-4.37	-5.12	-0.76	-6.08	-6.61	-0.53	-11.85	-11.96	-0.11	-11.98	-12.30	-0.32
7Y	-3.60	-3.60	0.00	-5.47	-5.42	0.05	-11.57	-11.39	0.18	-11.40	-11.62	-0.22
8Y	-3.29	-3.06	0.23	-5.14	-4.76	0.38	-11.23	-10.23	1.00	-10.79	-10.43	0.36
9Y	-3.14	-2.92	0.22	-4.90	-4.52	0.38	-10.67	-9.66	1.00	-10.06	-9.70	0.36
10Y	-2.96	-2.74	0.22	-4.63	-4.25	0.38	-9.84	-8.84	1.00	-9.16	-8.80	0.36
12Y	-2.24	-2.02	0.22	-3.74	-3.37	0.38	-7.58	-6.58	1.00	-6.95	-6.59	0.36
15Y	-0.98	-0.76	0.22	-2.37	-1.99	0.38	-5.14	-4.14	1.00	-4.74	-4.38	0.36
20Y	-0.25	-0.03	0.22	-2.10	-1.72	0.38	-5.16	-4.15	1.00	-5.24	-4.88	0.36
25Y	-0.25	-0.03	0.22	-2.10	-1.72	0.38	-5.16	-4.15	1.00	-5.24	-4.88	0.36
30Y	-0.25	-0.03	0.22	-2.10	-1.72	0.38	-5.16	-4.15	1.00	-5.24	-4.88	0.36

2021	Sep-21			Oct-21			Nov-21			Dec-21		
	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta
3M	-11.98	-12.55	-0.57	-13.46	-13.26	0.21	-16.71	-16.37	0.34	-2.40	-1.54	0.86
6M	-11.98	-12.55	-0.57	-13.46	-13.26	0.21	-16.71	-16.37	0.34	-2.40	-1.54	0.86
1Y	-11.98	-12.55	-0.57	-13.46	-13.26	0.21	-16.71	-16.37	0.34	-2.40	-1.54	0.86
2Y	-12.75	-13.31	-0.57	-14.58	-14.37	0.21	-20.09	-19.76	0.34	-21.22	-20.36	0.86
3Y	-13.12	-13.67	-0.56	-15.92	-15.25	0.67	-22.88	-21.58	1.30	-23.38	-21.40	1.98
4Y	-12.57	-13.15	-0.58	-14.69	-14.73	-0.04	-20.70	-20.37	0.33	-21.24	-20.27	0.97
5Y	-11.94	-12.39	-0.45	-13.59	-14.01	-0.42	-18.86	-19.10	-0.24	-19.07	-19.09	-0.02
6Y	-11.46	-11.64	-0.19	-12.92	-13.19	-0.27	-17.62	-18.03	-0.41	-17.43	-17.99	-0.56
7Y	-11.19	-11.17	0.02	-12.49	-12.56	-0.07	-16.65	-17.23	-0.58	-16.21	-17.00	-0.79
8Y	-10.89	-11.16	-0.27	-11.99	-12.34	-0.35	-15.64	-16.72	-1.09	-15.04	-16.19	-1.15
9Y	-10.41	-11.68	-1.27	-11.35	-12.63	-1.28	-14.55	-16.56	-2.01	-13.84	-15.68	-1.84
10Y	-9.76	-12.59	-2.83	-10.59	-13.16	-2.57	-13.43	-16.45	-3.02	-12.65	-15.20	-2.55
12Y	-8.03	-10.86	-2.83	-8.78	-11.35	-2.57	-11.20	-14.23	-3.02	-10.27	-12.82	-2.55
15Y	-6.25	-9.09	-2.83	-7.10	-9.67	-2.57	-9.46	-12.48	-3.02	-7.66	-10.21	-2.55
20Y	-6.89	-9.72	-2.83	-7.51	-10.08	-2.57	-9.74	-12.77	-3.02	-9.27	-11.82	-2.55
25Y	-6.89	-9.72	-2.83	-7.51	-10.08	-2.57	-9.74	-12.77	-3.02	-9.27	-11.82	-2.55
30Y	-6.89	-9.72	-2.83	-7.51	-10.08	-2.57	-9.74	-12.77	-3.02	-9.27	-11.82	-2.55

2022	Jan-22			Feb-22			Mar-22			Apr-22		
	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta
3M	-17.44	-17.79	-0.36	-22.75	-24.82	-2.07	-25.14	-28.46	-3.33	-37.48	-42.40	-4.93
6M	-17.44	-17.79	-0.36	-22.75	-24.82	-2.07	-25.14	-28.46	-3.33	-37.48	-42.40	-4.93
1Y	-17.44	-17.79	-0.36	-22.75	-24.82	-2.07	-25.14	-28.46	-3.33	-37.48	-42.40	-4.93
2Y	-21.40	-21.76	-0.36	-26.75	-28.82	-2.07	-29.95	-33.27	-3.33	-43.42	-48.34	-4.93
3Y	-22.33	-21.55	0.78	-28.35	-28.69	-0.34	-27.75	-30.53	-2.78	-39.83	-42.77	-2.95
4Y	-20.09	-19.79	0.29	-26.93	-27.20	-0.27	-24.47	-26.83	-2.36	-35.37	-37.51	-2.14
5Y	-18.04	-18.04	0.00	-25.06	-25.25	-0.19	-21.61	-23.18	-1.57	-31.37	-33.16	-1.79
6Y	-16.58	-16.56	0.03	-23.19	-23.18	0.01	-19.69	-20.37	-0.68	-28.50	-29.87	-1.37
7Y	-15.28	-15.38	-0.10	-21.11	-21.24	-0.13	-17.89	-18.13	-0.24	-26.07	-27.28	-1.22
8Y	-13.96	-14.50	-0.53	-19.02	-19.53	-0.51	-15.84	-15.80	0.04	-23.53	-25.12	-1.59
9Y	-12.77	-13.95	-1.18	-17.14	-18.08	-0.95	-13.80	-13.22	0.57	-20.95	-23.41	-2.46
10Y	-11.75	-13.42	-1.67	-15.50	-16.69	-1.19	-11.97	-11.05	0.92	-18.48	-22.62	-4.14
12Y	-9.94	-11.61	-1.67	-13.00	-14.19	-1.19	-9.20	-8.28	0.92	-14.44	-18.90	-4.46
15Y	-8.48	-10.15	-1.67	-11.69	-12.88	-1.19	-7.22	-6.30	0.92	-11.60	-16.06	-4.46
20Y	-8.74	-10.41	-1.67	-11.44	-12.63	-1.19	-6.57	-5.64	0.92	-10.20	-14.66	-4.46
25Y	-8.74	-10.41	-1.67	-11.44	-12.63	-1.19	-6.57	-5.64	0.92	-10.20	-14.66	-4.46
30Y	-8.74	-10.41	-1.67	-11.44	-12.63	-1.19	-6.57	-5.64	0.92	-10.20	-14.66	-4.46

2022	May-22			Jun-22			Jul-22			Aug-22		
	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta
3M	-29.90	-35.93	-6.03	-29.90	-35.93	-6.03	-32.57	-35.32	-2.76	-37.64	-43.25	-5.61
6M	-29.90	-35.93	-6.03	-29.90	-35.93	-6.03	-32.57	-35.32	-2.76	-37.64	-43.25	-5.61
1Y	-33.18	-39.22	-6.03	-33.18	-39.22	-6.03	-38.57	-41.32	-2.76	-45.98	-51.59	-5.61
2Y	-41.21	-46.83	-5.62	-41.21	-46.83	-5.62	-43.94	-45.78	-1.84	-48.01	-52.09	-4.08
3Y	-34.75	-39.17	-4.42	-34.75	-39.17	-4.42	-36.75	-38.23	-1.48	-41.19	-44.19	-3.00
4Y	-28.35	-31.84	-3.50	-28.35	-31.84	-3.50	-30.10	-31.59	-1.49	-34.36	-37.29	-2.93
5Y	-24.07	-26.02	-1.95	-24.07	-26.02	-1.95	-26.12	-26.72	-0.59	-29.81	-32.18	-2.37
6Y	-21.78	-22.00	-0.22	-21.78	-22.00	-0.22	-24.27	-23.60	0.67	-27.50	-28.83	-1.33
7Y	-20.04	-19.34	0.70	-20.04	-19.34	0.70	-22.75	-21.68	1.07	-25.45	-26.55	-1.10
8Y	-18.22	-17.93	0.29	-18.22	-17.93	0.29	-21.07	-20.54	0.53	-23.30	-24.75	-1.45
9Y	-16.37	-17.40	-1.03	-16.37	-17.40	-1.03	-19.38	-19.71	-0.32	-21.22	-23.08	-1.87
10Y	-14.62	-16.25	-1.63	-14.62	-16.25	-1.63	-17.84	-18.24	-0.40	-19.33	-21.32	-1.99
12Y	-11.75	-13.38	-1.63	-11.75	-13.38	-1.63	-15.37	-15.77	-0.40	-16.22	-18.20	-1.99
15Y	-7.71	-9.34	-1.63	-7.71	-9.34	-1.63	-11.55	-11.95	-0.40	-10.91	-12.90	-1.99
20Y	-5.59	-7.22	-1.63	-5.59	-7.22	-1.63	-10.06	-10.46	-0.40	-9.09	-11.08	-1.99
25Y	-5.59	-7.22	-1.63	-5.59	-7.22	-1.63	-10.06	-10.46	-0.40	-9.09	-11.08	-1.99
30Y	-5.59	-7.22	-1.63	-5.59	-7.22	-1.63	-10.06	-10.46	-0.40	-9.09	-11.08	-1.99

2022	Sep-22			Oct-22			Nov-22			Dec-22		
	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta	NonESG	ESG	Delta
3M	-40.87	-47.66	-6.79	-39.29	-44.99	-5.69	-29.91	-38.76	-8.85	-28.66	-38.31	-9.65
6M	-40.87	-47.66	-6.79	-39.29	-44.99	-5.69	-29.91	-38.76	-8.85	-29.22	-38.88	-9.65
1Y	-50.19	-56.98	-6.79	-51.68	-57.38	-5.69	-40.20	-49.06	-8.85	-38.07	-47.72	-9.65
2Y	-52.28	-55.91	-3.63	-51.06	-54.32	-3.26	-40.55	-43.84	-3.29	-38.99	-42.75	-3.76
3Y	-45.49	-47.34	-1.85	-42.49	-44.76	-2.27	-32.33	-33.42	-1.09	-30.13	-32.26	-2.12
4Y	-38.48	-40.15	-1.66	-33.43	-36.02	-2.59	-22.46	-24.36	-1.89	-19.31	-22.29	-2.98
5Y	-33.83	-34.94	-1.11	-26.59	-29.43	-2.83	-15.45	-17.44	-1.99	-10.78	-14.18	-3.40
6Y	-31.35	-31.63	-0.29	-22.50	-25.15	-2.65	-11.98	-13.15	-1.17	-6.02	-9.01	-2.99
7Y	-29.26	-29.51	-0.25	-19.80	-22.32	-2.52	-10.03	-11.01	-0.98	-3.46	-6.43	-2.98
8Y	-27.39	-27.83	-0.44	-18.01	-20.11	-2.10	-8.82	-9.69	-0.87	-2.07	-4.85	-2.79
9Y	-25.82	-26.24	-0.42	-16.84	-18.25	-1.41	-8.00	-8.25	-0.24	-1.45	-3.41	-1.96
10Y	-24.43	-24.72	-0.29	-15.93	-17.05	-1.12	-7.24	-6.98	0.26	-1.24	-3.02	-1.77
12Y	-21.49	-21.79	-0.29	-13.51	-14.64	-1.12	-4.76	-4.50	0.26	0.04	-1.73	-1.77
15Y	-15.01	-15.30	-0.29	-6.82	-7.94	-1.12	1.43	1.69	0.26	6.38	4.61	-1.77
20Y	-11.93	-12.22	-0.29	-4.22	-5.35	-1.12	3.21	3.48	0.26	7.97	6.19	-1.77
25Y	-11.93	-12.22	-0.29	-4.22	-5.35	-1.12	3.21	3.48	0.26	7.97	6.19	-1.77
30Y	-11.93	-12.22	-0.29	-4.22	-5.35	-1.12	3.21	3.48	0.26	7.97	6.19	-1.77

Figure 3.11: Kreditanstalt fuer Wiederaufbau: ESG vs Non ESG

Upon a brief analysis of the two tables, it is evident that the Z-spreads of the ESG bonds issued by both entities are generally lower than those of their conventional peers.
This outcome results in a negative Delta Z-spread (highlighted in red in the tables), which stands in contrast to previous observations made on the Z-spread time series.

Regarding these two key issuers, in terms of issuance volumes and bank's exposure, ESG bonds seem to be perceived as less risky investments than the associated conventional bonds. Consequently, ESG bonds have a lower value in terms of price.

This observation suggests that the ESG premium, which may encourage investors to buy ESG bonds, appears to diminish in the case of major issuers.
This finding provides a preliminary indication of the conclusive results that will be obtained through the quantitative methods adopted later.

4 | Classification Algorithms

Machine Learning (ML) is the sub-field of Artificial Intelligence (AI) where knowledge comes from experience and induction. Machines are able to extract information from data, during the training phase, and then to apply the acquired knowledge to unseen data.

There exist three different learning paradigms that can be implemented in ML:

- **Supervised** learning [13]: for problems where the available data consists of labeled examples, meaning that each data point contains features (covariates) and associated labels. The goal of supervised learning algorithms is learning a function that maps feature vectors (inputs) to labels (output), based on example input-output pairs.
- **Unsupervised** learning [38]: type of algorithm that learns patterns from untagged data. The machine is forced to build a concise representation of its world and then generate imaginative content from it.
  In contrast to supervised learning, where data is labeled by an expert, unsupervised methods exhibit self-organization that captures patterns as probability densities or a combination of neural feature preferences encoded in the machine's weights and activations.
- **Reinforcement** learning [37]: area of machine learning concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward.
  Reinforcement learning differs from supervised learning in not needing labelled input/output pairs to be presented, and in not needing sub-optimal actions to be explicitly corrected. Instead, the focus is on finding a balance between exploration (of uncharted territory) and exploitation (of current knowledge).

The paradigm I use is the supervised learning, since the variables selected for the ML methods adopted are labeled accordingly to their values.

For instance, Z-spread will be tagged into two or four categories as needed:

- high (H) / low (L), for binary classification performed through Logistic Regression;
- very low (LL) / low (L) / high (H) / very high (HH), for multi-class classification performed through Neural Networks.

Therefore, what I aim to do is trying to classify the Z-spread, that will be my target variable, of some unseen data through a model trained on the labeled data, using as co-variates some variables on which the Z-spread is known to depend and testing whether being ESG is among those crucial features in determining the level of spread.
I apply a binary classification algorithm at first, which embeds a Logistic Regression model and considers the 2-labels version of the Z-spread (H/L) as the dependent variable to be classified, then I resort to multi-class classification, using Neural Networks and the 4-labels version of the Z-spread (HH/H/L/LL).

The metric adopted to assess the quality of all these models is the Accuracy, which is defined through the Confusion Matrix that, in the simplest case of binary classification, is defined as follows:

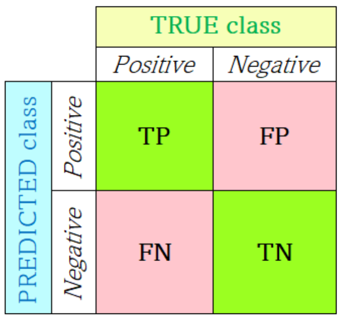


Figure 4.1: Confusion Matrix for Binary Classification

Where we define:

- True Positive (TP): data that belong to the positive class and that are correctly classified as positive by the model;
- True Negative (TN): data that don't belong to the positive class and that are correctly classified as negative by the model;
- False Positive (FP): data that belong to the negative class and that are wrongly classified as positive by the model;

- False Negative (FN): data that belong to the positive class and that are wrongly classified as negative by the model;

The accuracy is then defined as the ratio of data that are correctly classified by the model:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The extension of these notions to multi-class classification is quite straightforward, let's see it through an example to make it clearer.
Consider the 4-labeled Z-spread variable and imagine that the classifier model gave "L" as output, with the following classification outcome:

		TRUE class			
		LL	*L*	*H*	*HH*
PREDICTED class	*LL*	75	6	10	9
	L	**18**	**50**	**12**	**20**
	H	20	4	65	11
	HH	2	5	3	90

Figure 4.2: Confusion Matrix for Multi-Class Classification

Then we compute the values TP, TN, FP, FN in this way:

- $TP = 50$,
  the bonds with spread L that are correctly classified as such;
- $TN = (6 + 10 + 9) + (20 + 4 + 11) + (2 + 5 + 3) = 70$,
  the bonds with spread different from L that are classified as LL, H or HH;
- $FP = 18 + 12 + 20 = 40$,
  the bonds with spread different from L that are wrongly classified as L;
- $FN = 18 + 20 + 2 = 40$,
  the bonds with spread L that are wrongly classified as LL, H or HH.

Finally, the accuracy is: $$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{50+70}{50+70+40+40} = 60\%$$

The last theoretical building block that is missing to fully understand the Machine Learning techniques developed in the sequel is the so-called "bias-variance" trade-off.
In the context of statistical modeling and machine learning, "overfitting" and "underfitting" are terms used to describe the performance of a model in relation to the data it has been trained on.

Overfitting occurs when a model is too complex or flexible, and it learns the noise in the training data, rather than the underlying patterns. This can lead to a model that performs very well on the training data, but poorly on new, unseen data. In other words, the model "memorizes" the training data, instead of generalizing from it. This can be also referred to as "low bias, high variance", because the model fits the data too closely and has a high variance.

Underfitting, on the other hand, occurs when a model is too simple or inflexible, and it fails to capture the underlying patterns in the data. This can lead to a model that performs poorly on both the training data and new, unseen data. In other words, the model does not learn enough from the training data to be able to generalize to new data. This can be also referred to as "high bias, low variance", because the model does not fit the data closely enough and has high bias.

The goal of modeling is to find the sweet spot between overfitting and underfitting, where the model is complex enough to capture the underlying patterns in the data, but not so complex that it learns the noise in the data. This can be achieved through techniques such as regularization, cross-validation, and hyperparameter tuning.

Now that the theoretical background has been clarified, the goal of justifying the systematically higher ESG Z-spread previously observed will be pursued with this procedure:

- Start from the "Balanced" dataset (EU and KFW bonds excluded).
- Identify the target variable, which will almost always be the Z-spread, and the covariates, which will mostly be *ESG_Flag*, *Sector*, *Outstanding Amount*, *Country.Of.Risk* and the *Rating* of both the bonds and the issuers.
- Divide the numerical variables in bands, through quantiles of their empirical distributions, and transform the categorical variables in numeric with some encoding, which will differ accordingly to the specific model.
- Create a sub-sample of data with monthly observations that contains the selected variables and loop on the months from January, 2021 to November, 2022.
- Divide this sub-sample in a training set, used to train the models, and a test set, used to assess their quality (usual training-test split ratio: 80% - 20%).
- Train the supervised machine learning models on the training sample by adjusting the weights assigned to each input feature to minimize the difference between its predicted output and the actual one. In this crucial step, the models acquire the knowledge through which they are able to classify unseen data.
- Evaluate the quality of the models by measuring how well they performs at classifying new, unseen data. This is typically done by comparing the model's predicted output to the actual output and calculating a metric that reflects the model's performance, that in my case will be the accuracy defined above.
- Tune the hyperparameters of each specific model, by trying different versions and choosing the set of parameters that maximizes the performance on test data.
  Hyperparameters are set before training the model and control various aspects of the learning process. Some examples are the learning rate[1] , the regularization strength[2] , or the number of hidden layers in an ANN (see Section 4.2 *Artificial Neural Network* for more details).

---

[1]The learning rate is a tuning parameter in an optimization algorithm that determines the step size at each iteration while moving toward a minimum of a loss function.

[2]Regularization is a form of regression that shrinks the coefficient estimates towards zero. In other words, this technique discourages learning a more complex or flexible model, so as to avoid the risk of overfitting (the phenomenon whereby the model, being too complex, also fits weights to the noise of the training data and consequently loses the ability to generalize its knowledge to unseen data).

4.1. 2-Class Logistic Regression

A 2-class logistic regression is a statistical method used for binary classification, which consists in finding the probability of some event success and failure.
It's a type of generalized linear model that is used when the dependent variable is binary (e.g. 0/1, True/False, Yes/No).
The probability that the outcome is in one class or the other is modeled using the logistic function, which gives outputs between 0 and 1.
Let's start to understand the simplest case, in which we have a single covariate, then we'll extend the explanation to the multivariate case, with multiple covariates.

To fully understand the logistic regression model, a step back on the basic linear regression model is necessary.

The basic idea behind linear regression is to find the line of best fit that represents the relationship between a dependent variable Y and one or more independent variables X. In the case of simple linear regression with one independent variable X, the model can be represented as:

$$Y = \beta_0 + \beta_1 \cdot X + \epsilon$$

where Y is the dependent variable, X is the independent variable, β_0 is the intercept, β_1 is the slope coefficient, and ϵ is the error term.

The goal of linear regression is to estimate the values of the intercept and slope coefficients that minimize the Sum of Squared Errors (SSE) between the predicted values and the actual values of the dependent variable:

$$(\hat{\beta}_0, \hat{\beta}_1) = \arg\min_{\beta_0,\beta_1}\{SSE\} = \arg\min_{\beta_0,\beta_1}\{\frac{1}{2} \cdot \sum_{i=1}^{N} [y_i - \hat{y}_i]^2\} = \arg\min_{\beta_0,\beta_1}\{\frac{1}{2} \cdot \sum_{i=1}^{N} \epsilon_i^2\}$$

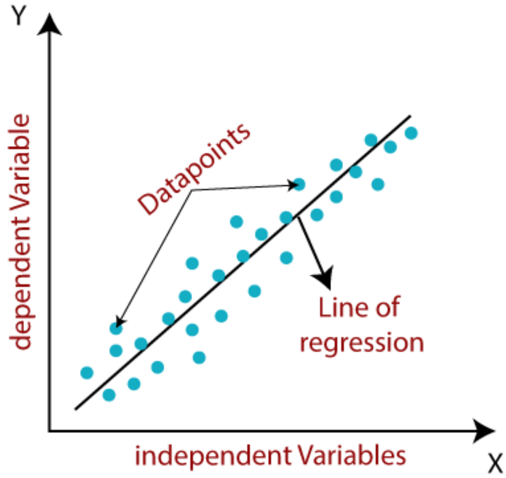


Figure 4.3: Linear Regression.

In other words, SSE measures the sum of squared distances among data points and the regression line. This is the quantity we should minimize; the introduction of the square is essential, otherwise distances of the points to the right of the regression line would compensate the ones of points to the left.

Logistic Regression (LR) is a generalized linear regression model that is used for binary classification problems, where the dependent variable Y can belong to two classes.
The LR model uses a logistic function to model the probability that Y belongs to the first class (C_1), given a set of independent variables X, which is given by:

$$\mathbb{P}(Y \in C_1|X) = \sigma(X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot X)}}$$

where $\sigma(X)$ is the predicted probability that Y belongs to C_1, given the values of the independent variables X, β_0 is the intercept, β_1 is the slope coefficient, and e is the base of the natural logarithm.

To estimate the values of the intercept and slope coefficients, we use a Maximum Likelihood Estimation approach (MLE). The likelihood function is defined as the product of the probabilities of the observed values of Y, given the values of X and the estimated parameters β_0 and β_1, which are modelled via a Bernoulli distribution:

$$\mathcal{L}(\beta_0, \beta_1) = \sigma(X)^Y + [1 - \sigma(X)]^{(1-Y)} \tag{4.1}$$

$$= \left[\frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot X)}}\right]^Y + \left[\frac{e^{-(\beta_0 + \beta_1 \cdot X)}}{1 + e^{-(\beta_0 + \beta_1 \cdot X)}}\right]^{1-Y} \tag{4.2}$$

where Y is the observed value of the target variable.

The log-likelihood function, which is the function that is actually maximized in the algorithm, is then defined as the natural logarithm of the likelihood function:

$$l(\beta_0, \beta_1) = Y \cdot \log[\sigma(X)] + (1 - Y) \cdot \log[1 - \sigma(X)].$$

The goal of logistic regression is to estimate the values of the intercept and slope coefficients that maximize the log-likelihood function.
This is typically done using an iterative algorithm, such as Gradient Descent, which adjusts the values of the coefficients to find the values that minimize the negative log-likelihood function.

Let's say we have a function $f(x)$ that we want to minimize. We can start with an initial value for the parameter x, denoted by x_0. The goal of Gradient Descent is to find the value of x that minimizes the function $f(x)$:

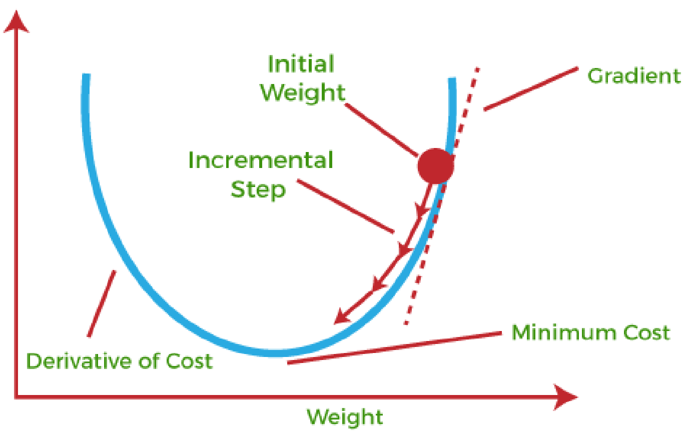


Figure 4.4: Gradient Descent Algorithm Visualization.

Algorithm 1 Gradient Descent

1: *Compute the gradient of the function at x_0*
The Gradient of a function is the vector of partial derivatives with respect to each of its parameters. In the case of a single parameter, the gradient is simply the derivative of the function with respect to that parameter.
Mathematically, the gradient of the function $f(x)$ at x_0 is given by:

$$\nabla f(x_0) = \frac{\partial f(x_0)}{\partial x}$$

2: *Update the value of x*
The idea is to update the value of x in the direction of the negative gradient, as this will take us towards the minimum of the function. This is done by subtracting a fraction of the gradient, called the "learning rate" and denoted by α, from the current value of x.
Mathematically, the updated value of x is given by:

$$x_1 = x_0 - \alpha \cdot \nabla f(x_0)$$

3: *Repeat steps 1 and 2 until convergence*
We repeat steps 1 and 2 for multiple iterations until we reach a convergence criteria, such as a maximum number of iterations or a small change in the value of the function.
Mathematically, we can express the iterative update rule for Gradient Descent as:

$$x_{i+1} = x_i - \alpha \cdot \nabla f(x_i)$$

where i is the iteration number.

The extension to the vectorial case is done by introducing the following terms:

- C1, C2 are the two classes of our binary classification problem;
- $\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2, ..., \beta_N)$ is the vector of coefficients of the regression model;
- $\boldsymbol{X} = (X_1, X_2, ..., X_N)$ is the vector of covariates (or features);

The probability of Y belonging to the two classes will thus be:

$$\mathbb{P}(\boldsymbol{Y} \in C_1|\boldsymbol{X}) = \sigma(\boldsymbol{\beta}^T \cdot \boldsymbol{X}), \qquad \mathbb{P}(\boldsymbol{Y} \in C_2|\boldsymbol{X}) = 1 - \mathbb{P}(\boldsymbol{Y} \in C_1|\boldsymbol{X}), \tag{4.3}$$

where σ is the sigmoid or logistic function already introduced above:

$$\sigma(\xi) = \frac{1}{1 + e^{-\xi}}$$

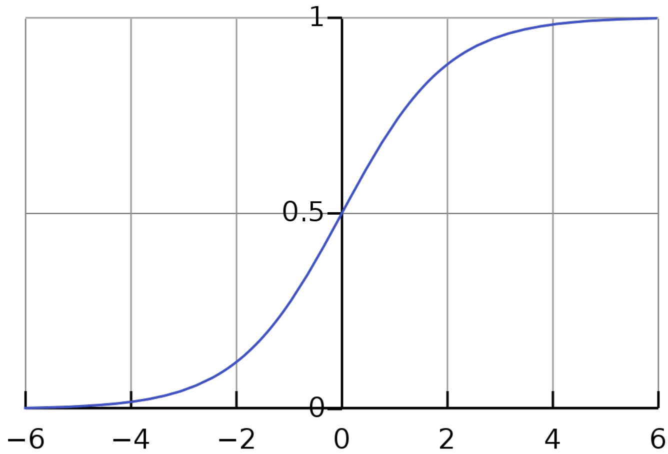


Figure 4.5: Sigmoid function.

As already said above, the logistic regression model is fitted using a MLE approach with a likelihood function modelled through a Bernoulli distribution:

$$\mathcal{L}(\boldsymbol{Y}|\boldsymbol{\beta}, \boldsymbol{X}) = \prod_{i=1}^{N} (p_i^{C_1})^{Y_i} \cdot (1 - p_i^{C_1})^{1-Y_i}$$

$$l(\boldsymbol{Y}|\boldsymbol{\beta}, \boldsymbol{X}) = \sum_{i=1}^{N} [Y_i \cdot log(p_i^{C_1}) + (1 - Y_i) \cdot log(1 - p_i^{C_1})]$$

where:

$$p_i^{C_1} = \mathbb{P}(Y_i \in C_1 | X_i, \boldsymbol{\beta}) = \sigma(\boldsymbol{\beta}^T \cdot X_i) = \sigma(\begin{pmatrix} \beta_1 \\ \vdots \\ \beta_n \end{pmatrix}^\top \cdot \begin{pmatrix} 0 \\ \vdots \\ X_i \\ \vdots \\ 0 \end{pmatrix}) = \sigma(\beta_i \cdot X_i) = \frac{1}{1 + e^{-\beta_i \cdot X_i}},$$

i.e. there is an underlying logistic function for the conditioned class probability.

The logistic function relates the probability of the outcome to the predictor variables in the form of a linear combination. The linear combination is then transformed by the logistic function to produce the probability.
Once the model is trained, it can be used to predict the probability of the outcome for new data points. These predictions can then be thresholded to produce binary classifications.

4.2. Artificial Neural Network

Artificial Neural Networks (ANNs) are a subset of machine learning techniques which are inspired by the human brain. Indeed, they mimic how biological neurons communicate with each other to come up with a decision.

The simplest form of a neural network is the so-called "Perceptron" model, proposed for the first time by Frank Rosenblatt in the late 1950s and still widely used today in machine learning applications. It is a computational model consisting of a single layer of artificial neurons, also known as perceptrons, which is based on the following key points:

- Distributed among simple non-linear units, the neurons themselves;
- Redundant, thus it is "fault-tolerant" since it can continue to make accurate predictions even if some of its individual perceptrons fail or are removed from the model;
- Intrinsically parallel, thus it is fast and efficient.

Each perceptron takes a set of input values and produces a single output value. The perceptron works by applying weights to the input values and then summing them up to produce a weighted sum. This sum is then passed through an activation function, which determines the output of the perceptron.

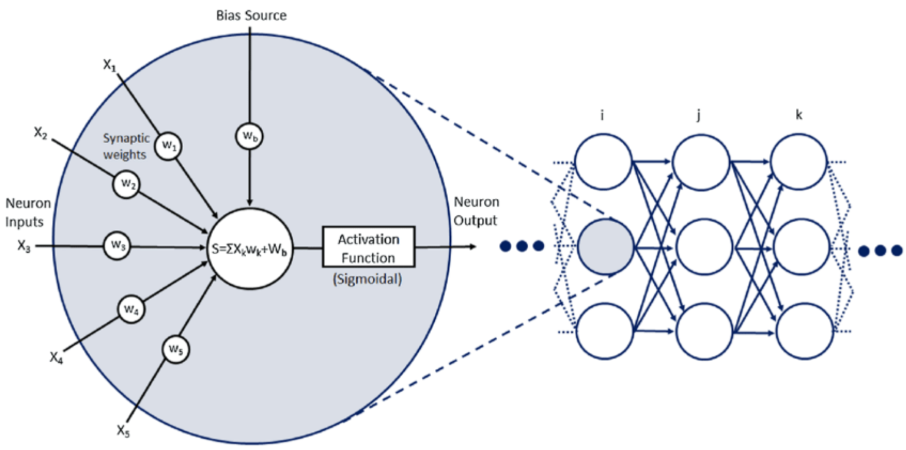


Figure 4.6: Scheme of a Neuron.

The weights w_i are updated during the training process, whose goal is to find the optimal set $\{\hat{w}_i\}_{i=1,...,N}$ that minimize the error between the predicted outputs and the actual ones.

However, the Perceptron model has limitations: it can only perform linear classification tasks and is unable to learn complex non-linear patterns in data.
In the 1980s, the Back-Propagation algorithm was developed, which enabled Artificial Neural Networks to learn more complex patterns and perform more demanding tasks. This algorithm allowed for multi-layer Neural Networks, also called "Multi-Layer Perceptrons" (MLPs), to be trained and used for classification and prediction tasks.

A multi-layer Neural Network consists of a series of collections of neurons, called "layers", that communicate to each other. In particular, there are three types of layers:

- an **input layer**, that receives an exogenous input signal;
- some **hidden layers**, that process the input data;
- an **output layer**, that produces the result.

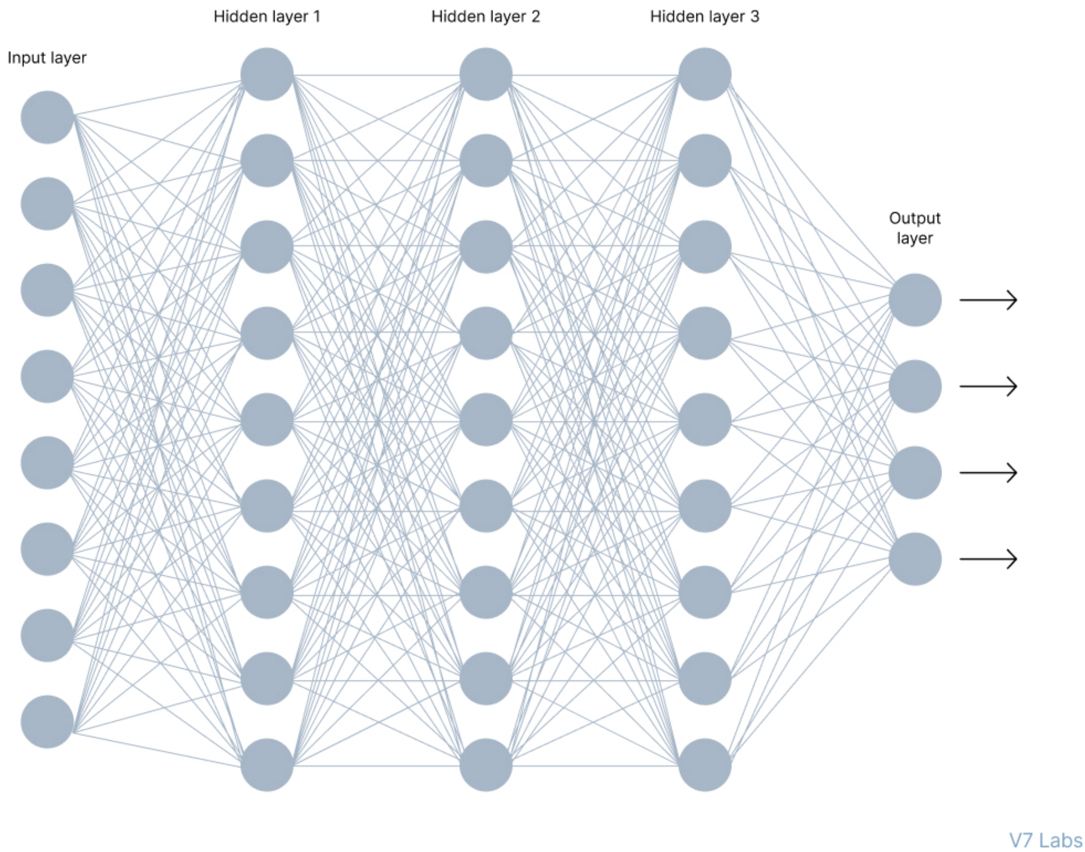


Figure 4.7: Artificial Neural Network Architecture

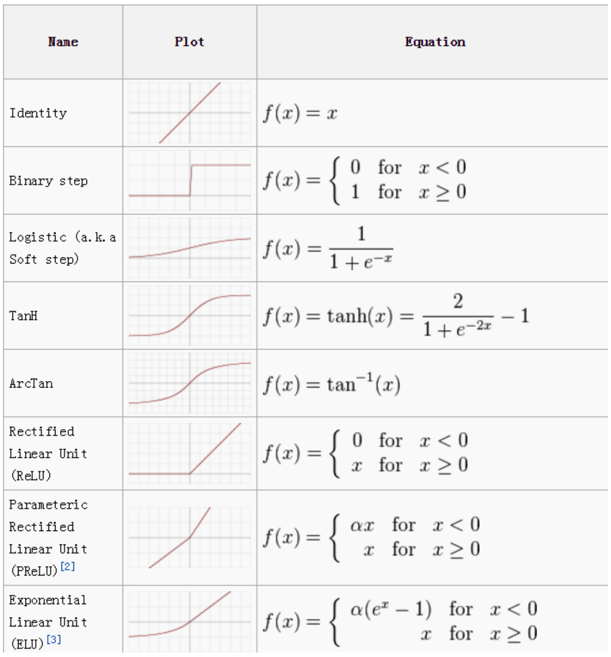
Consider a generic "hidden" neuron, i.e. a neuron in one of the middle layers of the Neural Network (neither an input-layer neuron, nor an output-layer one): it is connected to the N neurons of the previous layer, and it takes as input all the N outputs of such neurons. We denote these values with $\{x_i\}_{i\in\{1,\dots,N\}}$, while $\{w_{i,j}\}_{i\in\{1,\dots,N\}}$ are the weights associated to those values for the j-th neuron of the hidden layer considered.
Thus, the input function S of the j-th neuron is a weighted sum of previous layer outputs, plus the so-called "bias" term which represents the exogenous noise that affects each single layer of the ANN, independently from its units:

$$S_j = \sum_{i=1}^{N} w_{i,j} \cdot x_i + w_b$$

The output function of the j-th output neuron can be written as:

$$h_j(\mathbf{x}|\mathbf{w}, b) = h_j(S_j) = h_j(\sum_{i=1}^{N} w_i \cdot x_i + w_b)$$

where h_j is the "activation function" of the j-th neuron, that can be of different types:



Name	Plot	Equation
Identity		$f(x) = x$
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Logistic (a.k.a Soft step)		$f(x) = \frac{1}{1+e^{-x}}$
TanH		$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1$
ArcTan		$f(x) = \tan^{-1}(x)$
Rectified Linear Unit (ReLU)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$
Parameteric Rectified Linear Unit (PReLU) [2]		$f(x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$
Exponential Linear Unit (ELU) [3]		$f(x) = \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$

Figure 4.8: Activation functions

The choice of the activation function is particularly important for the output neurons and depends on the goal the ANN has been built for. Since my goal will be to perform a Binary or Multi-Label classification, I'll always use the Logistic (or Sigmoid) one.

Back-Propagation is a widely used algorithm for training Artificial Neural Networks. It is a supervised learning algorithm that enables ANNs to learn from labeled training data by adjusting the weights of the neurons. The algorithm is based on the chain rule of calculus and calculates the gradient of the loss function with respect to the weights of the network.

Here are the steps of the Back-Propagation algorithm, which will be described in details below:

- *Forward Pass*
  The input data is fed forward through the network to produce a prediction. Each neuron in the network computes a weighted sum of its inputs and applies an activation function to produce an output.
- *Calculate Error*
  The prediction is compared to the true label of the training example, and the error between them is calculated. The error is typically represented as a scalar value, such as the mean squared error.
- *Backward Pass*
  The error is propagated backwards through the network, and the gradient of the loss function with respect to the weights of the network is calculated using the chain rule of calculus. The gradient is used to update the weights of the network.
- *Update Weights*
  The weights of the network are updated using an optimization algorithm, such as stochastic gradient descent, which aims to minimize the loss function.

The gradient of the loss function with respect to the weights of the network is calculated using the chain rule of calculus, which states that the derivative of a composite function is equal to the product of the derivatives of its component functions. In the case of neural networks, the composite function is the output of the network, which is a function of the weights of the neurons.

Here is the mathematical formula for the chain rule:

$$\frac{\partial f(g(x))}{\partial x} = \frac{\partial f(g(x))}{\partial g(x)} \cdot \frac{\partial g(x)}{\partial x}$$

where f and g are two generic functions.

In the Back-Propagation algorithm, the gradient is calculated by recursively applying the chain rule to each layer of the network.

Here is the formula for the gradient of the loss function with respect to the weights:

$$\frac{\partial L}{\partial w_{ij}} = \frac{\partial L}{\partial o_i} \cdot \frac{\partial o_i}{\partial z_i} \cdot \frac{\partial z_i}{\partial w_{ij}}$$

where L is the loss function, o_i is the output of the i-th neuron, z_i is the weighted sum of the inputs to the i-th neuron, and $w_{i,j}$ is the weight between the i-th and j-th neurons.

The first term in the formula represents the error or loss of the network, the second term represents the derivative of the activation function of the neuron, and the third term represents the derivative of the weighted sum with respect to the weight.

The weights of the network are then updated during training using an optimization algorithm, such as Stochastic Gradient Descent (SGD). It works by updating the model's weights iteratively, based on the error between the predicted and actual outputs for a small random subset of the training data at each iteration. The random selection of training data subsets helps to prevent the algorithm from getting stuck in local minima and improve its convergence properties.

To sum up, if we consider a basic NN with just one hidden layer (referred to by subscript 1, while the output layer will be denoted with subscript 2), the complete Back-Propagation algorithm, with Stochastic Gradient Descent as updating rule, is as follows:

Algorithm 2 **Back-Propagation**

1: Select a random training example $(\mathbf{x}, y)$ from the dataset.

2: Compute the output of the neural network for the input $\mathbf{x}$:

- Compute the weighted sum of the inputs to each neuron in the hidden layer: $z_1 = \sum_{i=1}^{n} w_{i,1} x_i + b_1$
- Apply the activation function to each neuron in the hidden layer to produce the output: $h_1 = f(z_1)$
- Compute the weighted sum of the inputs to each neuron in the output layer: $z_2 = \sum_{j=1}^{m} w_{j,2} h_j + b_2$
- Apply the activation function to the output neuron to produce the predicted output: $\hat{y} = f(z_2)$

3: Compute the error between the predicted output $\hat{y}$ and the actual output y: $e = \hat{y} - y$

4: Compute the gradients of the weights with respect to the error:

- Compute the gradient of the weights in the output layer: $\frac{\partial E}{\partial w_{j,2}} = \frac{\partial E}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z_2} \cdot \frac{\partial z_2}{\partial w_{j,2}} = e \cdot f'(z_2) h_j$
- Compute the gradient of the bias in the output layer: $\frac{\partial E}{\partial b_2} = \frac{\partial E}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z_2} \cdot \frac{\partial z_2}{\partial b_2} = e \cdot f'(z_2)$
- Compute the gradient of the weights in the hidden layer: $\frac{\partial E}{\partial w_{i,1}} = \frac{\partial E}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z_2} \cdot \frac{\partial z_2}{\partial h_1} \cdot \frac{\partial h_1}{\partial z_1} \cdot \frac{\partial z_1}{\partial w_{i,1}} = e \cdot f'(z_2) \cdot w_{j,2} \cdot f'(z_1) \cdot x_i$
- Compute the gradient of the bias in the hidden layer: $\frac{\partial E}{\partial b_1} = \frac{\partial E}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z_2} \cdot \frac{\partial z_2}{\partial h_1} \cdot \frac{\partial h_1}{\partial z_1} \cdot \frac{\partial z_1}{\partial b_1} = e \cdot f'(z_2) \cdot w_{j,2} \cdot f'(z_1)$

5: Update the weights and biases using Stochastic Gradient Descent, with a learning rate α that is an hyperparameter of the model and, as such, can be tuned to achieve better performance:

- Update the weights in the output layer: $w_2 = w_2 - \alpha \cdot \frac{\partial E}{\partial w_2}$
- Update the bias in the output layer: $b_2 = b_2 - \alpha \cdot \frac{\partial E}{\partial b_2}$
- Update the weights in the hidden layer: $w_1 = w_1 - \alpha \cdot \frac{\partial E}{\partial w_1}$
- Update the bias in the hidden layer: $b_1 = b_1 - \alpha \cdot \frac{\partial E}{\partial b_1}$

6: Repeat steps 1-5 for a fixed number of epochs or until the error is below a certain threshold.

5 | Results

In this chapter there is the collection of the results obtained from the two main Machine Leaning models applied: Logistic Regressions and Artificial Neural Networks.

5.1. Logistic Regression Models

As previously stated, the logistic regression models' target variable is the Z-spread, which is dichotomized into two classes based on a daily-changing criterion. Specifically, a Z-spread value is classified as high (H) if it exceeds the weighted average of the Z-spreads for the outstanding capital on that given day, and low (L) if it falls below this threshold.

The following covariates are then considered in the analysis:

- *ESG_label*, which can take one of the two values "ESG" and "Non ESG".
- *Outstanding_label*, which is categorized into "High" and "Low", using the same logic as the one applied to the Z-spread.
- *Rating_label*, which is divided into three categories, namely "High", "Medium", and "Low" (this is the rating of the single bonds, not the issuers' ones). Following S&P's notation, a rating falls into the "High" category if it is between AAA and A-, "Medium" if it is between BBB and B-, and "Low" if it is between CCC and C-.
- *Country.Of.Risk*, which takes into account the risk of each country.
  This variable is encoded into a numeric one by considering the 5-Year Spread of the benchmark bonds (i.e., the most liquid ones), issued by each country's government. Here is the resulting categorization (from least (1) to most (5) risky):
  1. Switzerland, Netherlands, Germany, Sweden;
  2. Denmark, Finland, Belgium, Ireland;
  3. Portugal, Spain, Czech Republic, USA, Austria, Slovakia;
  4. Poland, Lithuania, Italy, South Africa, Greece;
  5. Turkey, Romania.

- *Industry*, which takes into account the sector of the reference issuer. This variable is not easy to transform in numeric, since the only piece of information that links it to the risk perception of the instrument is that Government and Financial Issuers' bonds have a lower credit spread than others. Thus, this variable has been kept categorical at this step, and then discarded from the following more advanced models.

The logistic regression models initially developed consider one regressor at a time, to assess its explanatory power individually. Finally, a model called "Ensemble" is developed, that considers all regressors together and is used as a benchmark for the performance of univariate models.

This is the evolution of the monthly accuracies of the different Logistic Regression models developed (for instance, "ESG Accuracy_LR" is the monthly accuracy of the univariate model which uses the *ESG_label* as unique covariate to classify the Z-spread of unseen data in its two possible categories "ESG" and "Non ESG"):

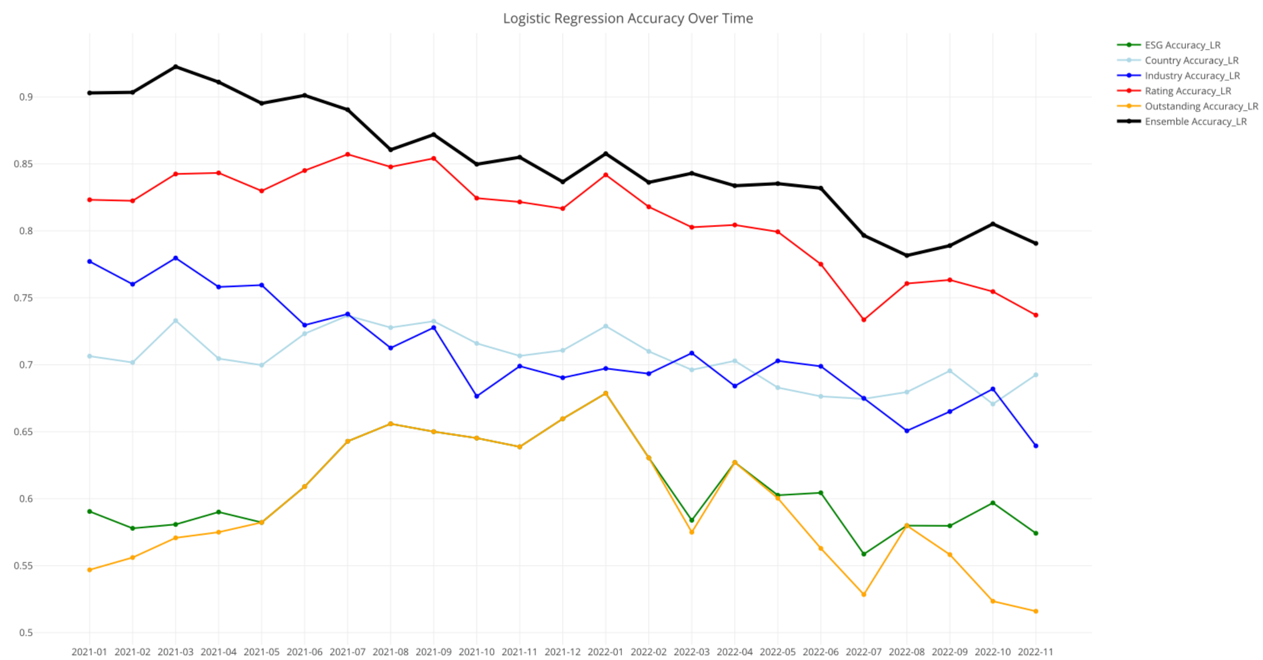


Figure 5.1: Logistic Regression Monthly Accuracy.

Let us begin by conducting an analysis of the "Ensemble" model accuracy, which is regarded as the benchmark for all other models, as it comprises all five selected covariates and thus has the highest attainable performance among the developed models.

At the outset of 2021, the accuracy of the model is roughly 92%. However, beginning in October 2021, with the onset of energy shock that heralds Russia's invasion of Ukraine, the accuracy of the model begins to exhibit a declining trend, which becomes increasingly apparent. Nevertheless, a slight recovery can be observed towards the end of 2022, leading to an accuracy that settles slightly above 80%. Given the period of great uncertainty in which the analysis is conducted and the simplicity of the adopted model, particularly in terms of the few selected covariates, this performance can be considered very satisfactory.

Moving on to the analysis of the univariate models, which consider one regressor at a time, it is evident that the bonds' *Rating* is by far the variable that best determines the Z-spread of the bond itself, to the point where it almost achieves the performance of the "Ensemble" model.

The remaining variables make only a minor contribution, in addition to the preponderant contribution of the *Rating*, with the *ESG_label* variable, in particular, proving to be one of the least effective in this regard.

Specifically, by creating an additional model that takes into account both *Rating* and *ESG_label* as covariates and comparing its performance with the two univariate models' ones, it is evident that the contribution of the ESG feature is basically null. In fact, it can be seen from the graph below that the accuracy of the 'Ensemble' model, i.e. the one using *Rating* and *ESG_label* as two covariates, is perfectly superimposed on that of the univariate model using *Rating* alone.

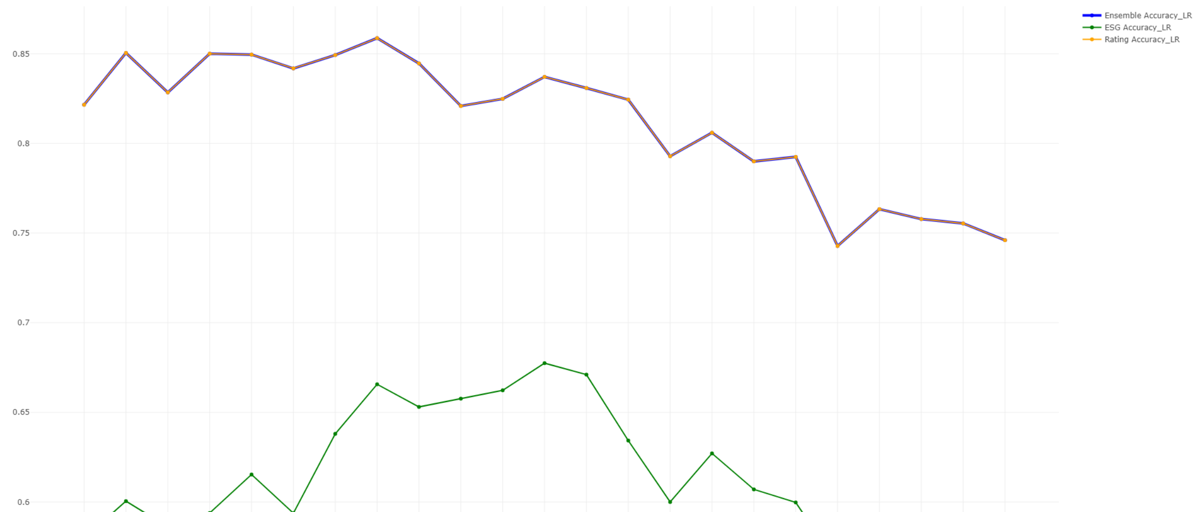


Figure 5.2: Logistic Regression Monthly Accuracy: Rating vs. ESG_Flag.

This fact contradicts the earlier conclusions drawn from the graphical analysis of the time series, which suggested that being ESG of a bond resulted in a systematic difference in Z-spread on average.

Consequently, it is worthwhile to pursue this analysis in two directions:

- Firstly, by refining the Z-spread distinction from two to four categories, which would provide greater granularity and enable better classification differences to be discerned.

- Secondly, by employing a more sophisticated and advanced classification method that can better interpret the patterns and dependencies among the data.

5.2. Artificial Neural Networks Models

Following the models developed earlier with logistic regression, I apply the same logic of comparing univariate models, which consider individual variables as regressors, to an "Ensemble" model, which instead considers them all together.
As already mentioned above, the variable *Industry_label*, whose aim was to take into account the risk associated to each sector in which bonds' issuers operate, will not be considered anymore from now on, given the difficulty to transform it into a numeric variable that is able to faithfully reflect the risk of different sectors.

5.2.1. ANN models For *Z.Spread_label* Classification

At this step, the aim still remains that of classifying the *Z.spread_label*, which is now however divided into four categories using quantiles of its daily empirical distribution:
0% - 25% $\Longrightarrow$ Very Low (LL);
25% - 50% $\Longrightarrow$ Low (L);
50% - 75% $\Longrightarrow$ High (H);
75% - 100% $\Longrightarrow$ Very High (HH).

With this increased granularity of Z-spread classes, it is obvious that the accuracy of these Neural Networks models will be lower than that of the logistic regressors. In that case with two classes, indeed, the random classifier has an accuracy of 50%, whereas with four classes, the random classifier will now have an accuracy of 25%.

After an hyperparameter tuning session, in which different versions of Neural Networks having different parameters were trained, this is the final form of NN models adopted:

```
nnet(Z.Spread_label ~ ., data=train_data, size = 5, MaxNWts = 100000, decay = 0.1, maxit = 100)
```

where *Z.Spread_label* is the target variable, *train_data* is the subset of monthly data randomly selected for training the model, *size* is the depth of the ANN (i.e. the number of hidden layers), *MaxNWts* is the maximum number of weights learnable by the model, *decay* is the parameter that controls L2 regularization [1], and *maxit* is the maximum number of training iterations.

[1] L2 regularization, also known as "Ridge regression", is a Machine Learning technique to prevent overfitting by adding a penalty term to the cost function that is proportional to the square of the magnitude of the model's weights. This penalty encourages the model to have smaller weights, which reduces the impact of individual features and helps to avoid overfitting. This technique is controlled through the learning decay parameter: a too large value can result in underfitting, whereas a too small value can provoke overfitting.

Here are the monthly accuracies of the models developed: recall that "Ensemble" model is the one which considers all covariates together, while "Rating", "Outstanding", "Country" and "ESG" are the univariate models that use just one covariate at a time.

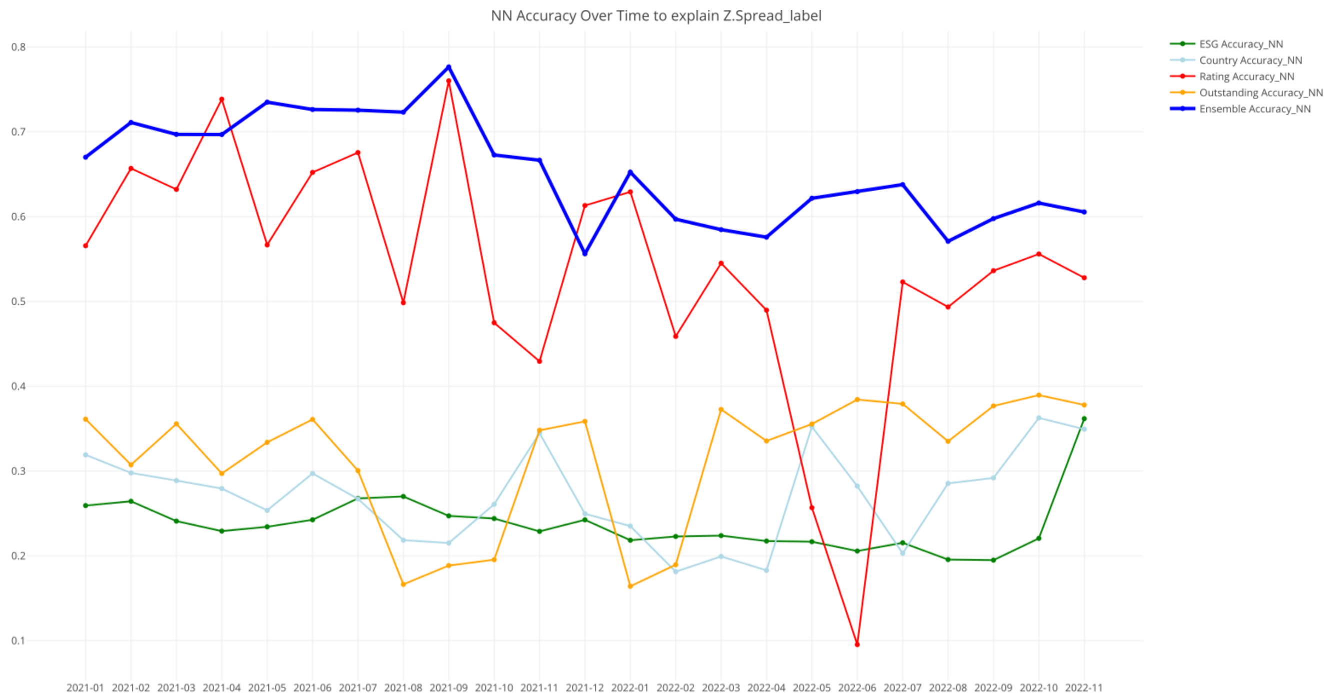


Figure 5.3: NN Accuracy Over Time to explain *Z.Spread_ label*

Beginning with an analysis of the performance of the "Ensemble" model, we observe that it fluctuates within a range of values spanning from 58% to 78%, with a notable peak in September 2021, followed by a customary downward trend in the subsequent months, and ultimately readjusting to approximately 60% by the end of the evaluation period.

In regards to the univariate models, a notable discrepancy is observed again between the *Rating* variable and the other covariates. Specifically, the *ESG_label* demonstrates a consistently low level of performance throughout the evaluation period, akin to that of a random classifier, with the exception of a relatively insignificant peak in the last evaluation month. It is noteworthy that, while the model employing solely the *Rating* variable as a covariate consistently approaches the performance of the ensemble model, surpassing it in April and December 2021 [2] , the explanatory power of this variable undergoes a precipitous decline in the months immediately following the outbreak of the conflict in Ukraine, only to recover from July 2022 onwards.

In order to assess the actual contribution of other variables, it is interesting to see if they are able to compensate for this drop in the *Rating* performance during that specific period. To do this, it is sufficient to construct Neural Networks models that take as input variables pairs containing the *Rating_label* and one other variable at a time, then evaluate their performance and see whether the bi-variate models are able to keep high their performance throughout the entire period.
These are the results obtained:

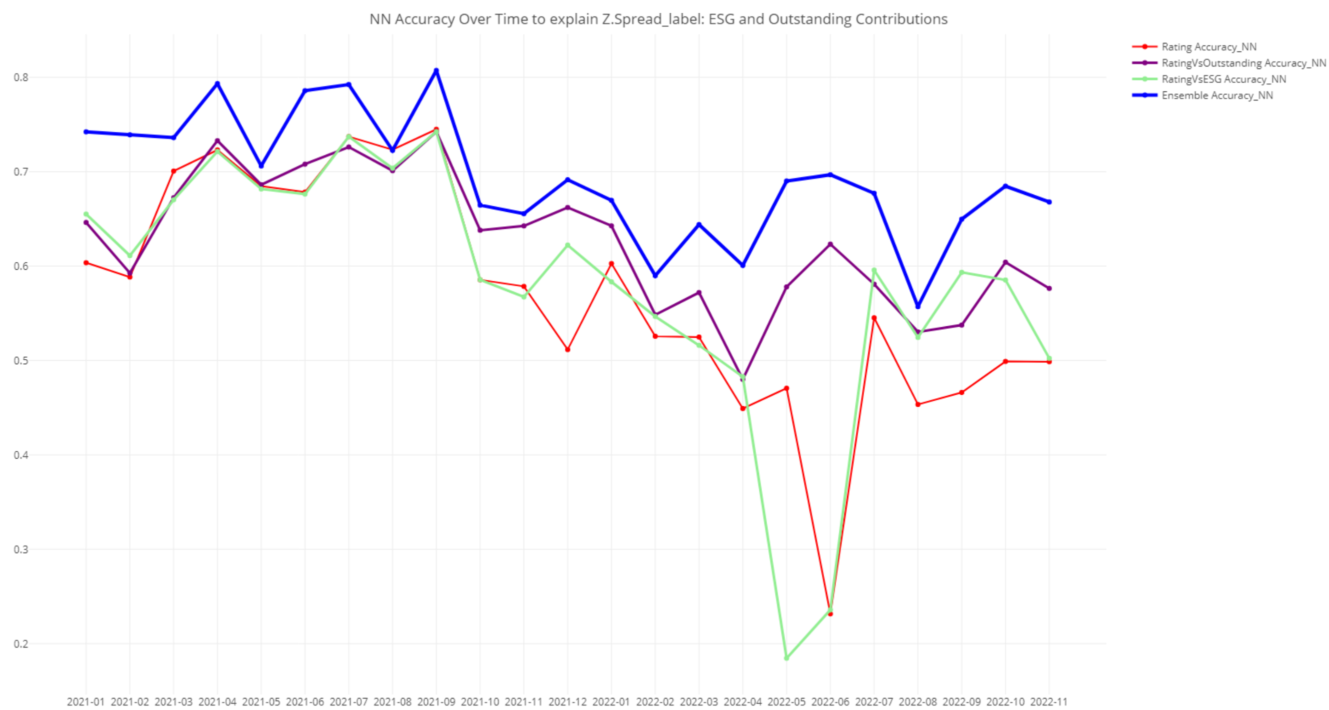


Figure 5.4: NN Accuracy Over Time to explain *Z.Spread_label*:
ESG_label and *Outstanding_label* Contributions

[2]The main reasons why a single-input model has a better accuracy than a multiple-input one are the correlation among input variables and noisy data contained in the additional variables, which might introduce some data dependencies that result in too much information to be learnt by the model.

It is evident from this graph that the contribution of the ESG variable is absolutely null, since the performance of the model which takes into account both *Rating* and *ESG_label* as covariates drops in correspondence to the *Rating*-only model's accuracy drop, whereas the *Outstanding_label* variable, on the other hand, proves to be the variable that keeps the model's performance high even when the rating drops.

This fact is absolutely in line with the results found by Beber, Brandt, and Kavajecz (1994) in their paper "Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market", a milestone in financial research.
The authors asserted that bond investors generally place great importance on the credit quality of bonds, but that in times of market stress they seek greater liquidity at the expense of quality.
This could be the reason why the *Rating*-*Outstanding* pair is able to satisfactorily classify the *Z-spread_label* of the bonds considered throughout the whole research period, surviving even very large market shocks like the one observed starting from February, 2022.

5.2.2. ANN models For *ESG_ label* Classification

Having received further confirmation of the total ineffectiveness of a bond's *ESG_ label* in determining its Z-spread, as opposed to the *Rating_ label*, it is time to turn the perspective around and address a new research question: can the issuer's rating, used as a covariate, classify that issuer's bonds into "ESG" and "Non ESG"?
In case the answer is positive, all the systematic Z-spread and price differences observed in the time series analysis done earlier would be attributable to the ESG type only indirectly, being actually determined by the Rating.

By developing Neural Network models similar to those described above:

```
nnet(ESG_label ~ ., data=train_data, size = 10, MaxNWts = 100000, decay = 0.1, maxit = 200)
```

with the difference that now the target variable becomes the *ESG_ label* of the bonds and the hyperparameters are slightly different (e.g. 10 hidden layers instead of 5, 200 maximum iterations instead of 100), the following results are obtained:

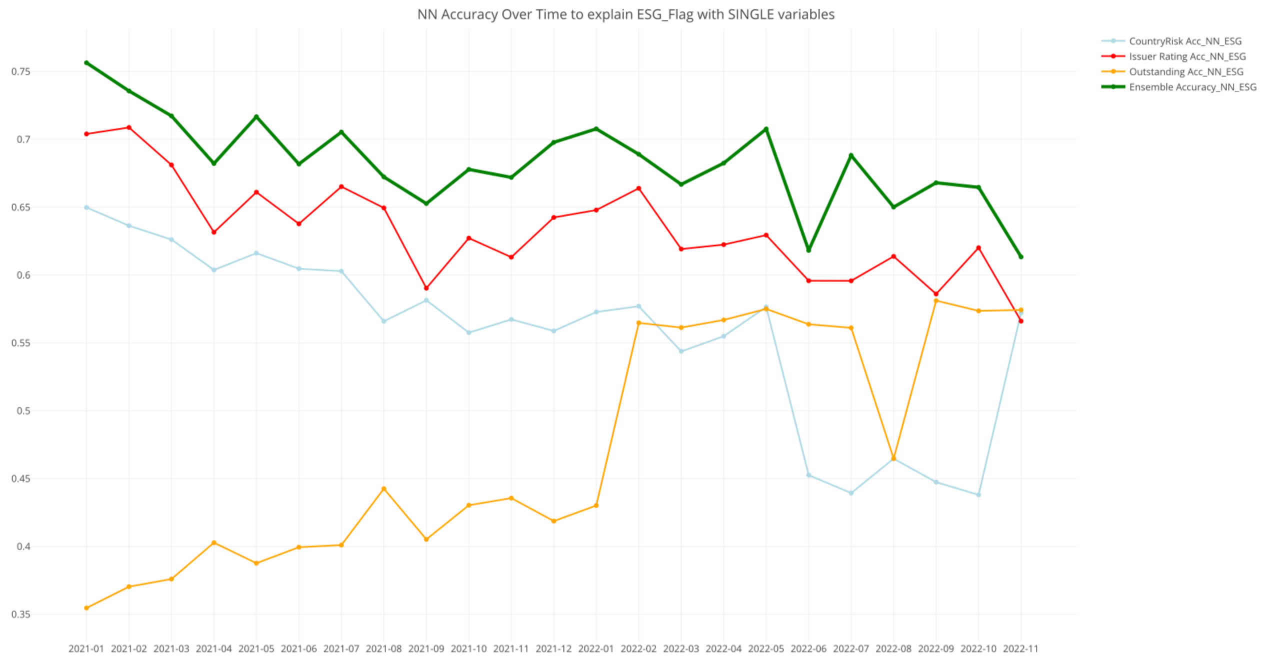


Figure 5.5: NN Accuracy Over Time to explain *ESG_ label*

Again, we obtain an "Ensemble" model with good performance (accuracy around 70%), and once again the Rating represents the variable with the greatest explanatory power among those selected, with classification accuracy hovering around 65%.
The other variables, used as single covariates, seem to be irrelevant. This fact thus confirms the hypothesis that the Rating of an issuer is able to satisfactorily classify the *ESG_ label* of a bond of the same issuer.

It is interesting to examine the association that the neural network has learned between the two variables, in order to identify any potential trend linking them.
From a financial perspective, obtaining and maintaining an ESG label for a security issuance is a significant expense for the issuer. This is due to the fact that it restricts the scope of investment of the revenues generated by the issuance and requires substantial effort in terms of audits, monitoring, and reporting to certify the issuer's commitment to Environmental, Social or Governance responsibility.

Therefore, an issuer with a high credit rating, capable of issuing bonds "paying" a low credit spread above the risk-free level, may have little incentive to pursue the rigorous ESG certification process. On the other hand, a low-rated issuer may be more willing to undertake the ESG certification process to enhance the attractiveness of its bonds to investors by attaining a Green, Sustainable, Social, or Sustainability-Linked label.

Using the "predict" functionality of the R package "nnet", we are able to associate with each rating class of an issuer the probability that its issues will be labeled as "ESG". This is the result:

Issuer Rating	**ESG Prob.**
B-	98.21%
B	86.81%
B+	74.64%
BB-	57.59%
BB	49.28%
BB+	46.56%
BBB-	45.12%
BBB	43.52%
BBB+	42.64%
A	41.94%
AA-	41.16%
AA	41.42%
AA+	41.16%
AAA	41.09%

Table 5.1: Probability of being "ESG" given *IssuerRating*.

As can be seen from this table, for issuers with low-to-medium creditworthiness, i.e. ranging from B- to A, there is a perfectly monotonic decreasing trend linking an issuer's rating and the probability of its issues being classified as ESG: the worse the former, the higher the latter.
Only high-creditworthiness issuers with rating AA- or better display no clear-cut relationship between rating and probability of issuing ESG bonds.

This finding allows us to suggest an answer to the new research question, confirming our hypothesis that low-rated issuers have an incentive to issue ESG to attract investors.
This result is also in line with what was found in the analyses carried out for the two 'unbalanced' issuers: European Union and Kreditanstalt für Wiederaufbau, rated AAA and AA+ by Standard & Poor's, respectively. For these important and well-rated issuers, we found a negative delta Z-spread between ESG and conventional bonds, i.e. no evidence of any kind of "ESG premium" that makes ESG bonds more attractive for investors.

6 | Conclusions and Future Developments

In light of the numerous analyses conducted on the large amount of data collected on ESG and non-ESG corporate bonds, it can be confidently concluded that there exists an ESG Premium, rendering ESG bonds more desirable to investors compared to their conventional counterparts.
This subsequently translates into a systematically lower price for ESG bonds, when compared to non-ESG ones. This differential further widened during the period of interest, especially in light of the increased volatility caused by the Russia-Ukraine conflict.

However, upon closer examination of the main drivers behind this difference in value, with the Z-spread of bonds as the target variable, it became apparent that being labelled as ESG is not as determinant as previously thought. As a matter of facts, the classification models trained using the *ESG_label* as the sole input variable yielded results comparable to those of a random classifier.

These results fully fit in with the stream of research mentioned in *Literature Review* section, from which it can be seen that no consensus has yet been reached on the fact that the Green or, more generally, ESG characteristic of a bond is decisive in making its yields or prices systematically lower than their conventional peers.

This findings, combined with the fact that the *ESG_label* failed to make any meaningful contribution to the performance achieved by the univariate models utilizing the *Rating* as an input variable to classify the Z-spread, led to the emergence of a second research question. The aim of this inquiry was to investigate whether the *Rating* of an issuer could train a Neural Network to classify the *ESG_label* of its issues.

The answer, in this instance, is affirmative, with compelling evidence indicating that the lowest ratings correspond to the highest probability that bonds issued by such entities are classified as ESG. Additionally, this correlation displays a monotonous trend, which associates the bonds of the highest-rated issuers with the lowest probability of being categorized as ESG.

It is evident that the ESG premium creates a clear division between lower and higher rated issuers in terms of costs and benefits of ESG certification. While lower rated issuers benefit from lower bond yields due to the ESG premium, higher rated issuers may not see the same benefits and are therefore discouraged from obtaining ESG certification.

This highlights the need to pay more attention to the benefits and costs of ESG certification for both lower- and higher-rated issuers. Indeed, the growth and consolidation of the ESG bond market, on the one hand, does not seem to provide an incentive for highly rated issuers to adopt sustainable initiatives based on a lower financing cost. On the other hand, it does offer an opportunity for lower-rated issuers willing to undertake sustainable initiatives due to the abundance of available funds.
An ESG premium, limited to low-rated issuers, could however also lead to an instrumental use of this market by companies that have no real interest in undertaking sustainable finance initiatives.

As a final piece of evidence, I report the numbers describing how many ESG bonds in my dataset have been issued in the period from 4 January 2021 to 22 November 2022, by issuers with both high ratings (from A- to AAA) and low ratings (from B- to BBB+), compared with conventional ones:

ESG Bonds Issuance Percentage

Issuer Rating	N° ESG Bonds	N° Non-ESG Bonds	ESG Issuance %
$\geq$ **A-**	235	331	41.52 %
$<$ **A-**	168	145	53.67 %

Table 6.1: ESG and Non-ESG bonds numbers in my dataset

The numbers presented serve as further confirmation of previously expressed findings. This is especially noteworthy given the exceptional value of the dataset utilized in the analysis, which was constructed using the tools provided by the prominent bank where I conducted my thesis work. As a result, the dataset provides a comprehensive overview of the European corporate bond market.

The interpretation of these results can be twofold.
The first is that the corporate bond market, while being an important tool to promote sustainable finance and corporate progress, may have been exploited by issuers with a lower credit rating as a way to attract financing, which would be more difficult to access through traditional bonds.
A second view could be that these lower-rated issuers, thanks to the booming market for ESG bonds, found a way to channel their efforts into implementing sustainable projects that, until then, they had not been able to put into practice.

What emerges quite clearly, however, is that established issuers with higher credit ratings have no incentive to undertake the complex and time-consuming bureaucratic process required to obtain and maintain ESG certification for their issues, as they already have access to financing at a low Z-spread above the risk-free level and do not need to attract investors. Moreover, given their great reputation, a Greenwashing[1] practice would result in a number of risks that would not be balanced at all by the possible benefits.

[1]Greenwashing is defined as "the process of conveying a false impression or misleading information about how a company's products are environmentally sound. Greenwashing involves making an unsubstantiated claim to deceive consumers into believing that a company's products are environmentally friendly or have a greater positive environmental impact than they actually do".
Source: [3].

Based on the research conducted, it can be concluded that the ESG landscape has experienced significant evolution in recent years. However, it appears insufficiently regulated and structured to fully and effectively achieve its intended purpose of improving the environmental situation and addressing the social challenges of our time.

In order to determine the true intentions behind ESG-labeled financial instruments, a thorough analysis is necessary before any investment is made. This is crucial to ensure that such instruments are genuinely aligned with virtuous objectives, and not simply a ploy for issuers to capitalize on the success of ESG and attract investment capital.

Bibliography

[1] Bloomberg: nel 2021 raddoppiato il debito sostenibile. https://www.eticanews.it/bloomberg-nel-2021-raddoppiato-il-debito-sostenibile/.

[2] Investment grade bonds. https://www.forbes.com/advisor/investing/investment-grade-bonds/.

[3] What is greenwashing? how it works, examples, and statistics. https://www.investopedia.com/terms/g/greenwashing.asp. Accessed: April 03, 2023.

[4] Margin. https://www.investopedia.com/terms/m/margin.asp.

[5] Lt2 definition. https://www.borsaitaliana.it/notizie/sotto-la-lente/obbligazioni-senior-subordinate119.htm.

[6] Feedforward vs. feedback neural networks. https://blog.paperspace.com/feed-forward-vs-feedback-neural-networks/.

[7] S&P 500 bond index. https://www.spglobal.com/spdji/en/indices/fixed-income/sp-500-bond-index/#overview. S&P Global website.

[8] SP green bond index. https://www.spglobal.com/spdji/en/indices/esg/sp-green-bond-index/#overview.

[9] Tlac definition. https://www.risk.net/definition/total-loss-absorbing-capacity-tlac.

[10] Credit risk. https://coebank.org/en/investor-relations/risk-management/credit-risk/#:~:text=Credit%20risk%20is%20defined%20as,accordance%20with%20the%20agreed%20terms. Accessed: March 29, 2023.

[11] Interest rate risk. https://www.investopedia.com/terms/i/interestraterisk.asp. Accessed: March 29, 2023.

[12] Spot rate curve. https://www.investopedia.com/terms/s/spotratecurve.asp. Accessed on March 29, 2023.

[13] Supervised learning — Wikipedia, the free encyclopedia, 2023. URL https://en.wikipedia.org/wiki/Supervised_learning. [Online; accessed 29-March-2023].

[14] E. Agliardi and R. Agliardi. Financing environmentally-sustainable projects with green bonds. *Environment and Development Economics*, 24(6):608–623, 2019. doi: 10.1017/S1355770X19000020.

[15] D. T. ÇETİN. Green bonds in climate finance and forecasting of corporate green bond index value with artificial intelligence. *Journal of Research in Business*, 7(1): 138–157, 2022.

[16] CNBC. COP27 leaders' speeches. CNBC website, November 9 2022. URL https://www.cnbc.com/2022/11/09/cop27-world-leaders-insist-ukraine-war-must-not-derail-climate-action.html.

[17] G. Gianfrate and M. Peri. The green advantage: Exploring the convenience of issuing green bonds. *Journal of cleaner production*, 219:127–135, 2019.

[18] B. Hachenberg and D. Schiereck. Are green bonds priced differently from conventional bonds? *Journal of Asset Management*, 19:371–383, 2018.

[19] I. C. M. A. (ICMA). Green bond principles (gbp). ICMA website, 2023. URL https://www.icmagroup.org/sustainable-finance/the-principles-guidelines-and-handbooks/green-bond-principles-gbp/.

[20] I. C. M. A. (ICMA). Sustainable finance principles. ICMA website, 2023. URL https://www.icmagroup.org/sustainable-finance/the-principles-guidelines-and-handbooks/.

[21] I. C. M. A. (ICMA). Sustainability bond guidelines (sbg). ICMA website, 2023. URL https://www.icmagroup.org/sustainable-finance/the-principles-guidelines-and-handbooks/sustainability-bond-guidelines-sbg/.

[22] I. C. M. A. (ICMA). Social bond principles (sbp). ICMA website, 2023. URL https://www.icmagroup.org/sustainable-finance/the-principles-guidelines-and-handbooks/social-bond-principles-sbp/.

[23] I. C. M. A. (ICMA). Sustainability-linked bond principles (slbp). ICMA website, 2023. URL https://www.icmagroup.org/sustainable-finance/the-principles-guidelines-and-handbooks/sustainability-linked-bond-principles-slbp/.

[24] International Energy Agency (IEA). Global coal consumption, 2000-2025. IEA web-

site, n.d. URL https://www.iea.org/data-and-statistics/charts/global-coal-consumption-2000-2025. Licence: CC BY 4.0.

[25] Investopedia. The basics of bonds. https://www.investopedia.com/financial-edge/0312/the-basics-of-bonds.aspx, March 2012.

[26] Investopedia. Corporate bond, n.d.. URL https://www.investopedia.com/terms/c/corporatebond.asp.

[27] Investopedia. Government bond, n.d.. URL https://www.investopedia.com/terms/g/government-bond.asp.

[28] Investopedia. Mortgage bond, n.d.. URL https://www.investopedia.com/terms/m/mortgage_bond.asp.

[29] Investopedia. Municipal bond, n.d.. URL https://www.investopedia.com/terms/m/municipalbond.asp.

[30] I. S. IPCC. *IPCC Special Report*. 2018.

[31] S. MacAskill, E. Roca, B. Liu, R. A. Stewart, and O. Sahin. Is there a green premium in the green bond market? systematic literature review revealing premium determinants. *Journal of Cleaner Production*, 280:124491, 2021.

[32] E. Nelson. Can bonds predict the direction of the economy? The Balance website, 2022. URL https://www.thebalancemoney.com/can-bonds-predict-the-direction-of-the-economy-416906.

[33] G. Peters, R. Zhu, G. Tzougas, G. Rabitti, and I. Yusuf. The role and significance of green bonds in funding transition to a low carbon economy: A case study forecasting portfolios of green bond instrument returns. *Available at SSRN 4299196*, 2022.

[34] Stata. Structural breaks in time series data. https://www.stata.com/features/overview/structural-breaks/#:~:text=It's%20called%20a%20structural%20break,process%20that%20produce%20the%20series., n.d.

[35] Statology. Chow test: Definition, examples, and interpretation. https://www.statology.org/chow-test/, 2021. [Online; accessed 29-March-2023].

[36] United Nations Framework Convention on Climate Change. COP26 UN Report, 2021. URL https://www.un.org/en/climatechange/cop26.

[37] Wikipedia. Reinforcement learning — Wikipedia, the free encyclopedia, 2023. URL https://en.wikipedia.org/wiki/Reinforcement_learning. [Online; accessed 29-March-2023].

[38] Wikipedia. Unsupervised learning — Wikipedia, the free encyclopedia, 2023. URL https://en.wikipedia.org/wiki/Unsupervised_learning. [Online; accessed 29-March-2023].

[39] O. D. Zerbib. The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking & Finance*, 98:39–60, 2019.

A | What Is A Bond?

A bond is a fundamental financial instrument that represents the liability of the issuer, whether it is a company or a government. These obligations are divided and sold to investors in smaller units, which are known as bonds issued by the issuer itself [25].

When an individual purchases a share, they acquire a small stake in the company and become a shareholder, actively participating in the company's growth and losses.
Conversely, a bond is a type of loan where a company can issue a bond to obtain funding for various reasons.

Similar to a home mortgage, a fixed amount of money is borrowed for a predetermined period. At maturity, the bond is paid back in full, including the agreed-upon notional amount at issuance, and during that period, the company pays the investor a fixed amount of interest, known as the "coupon", on set dates, such as quarterly.

A.1. Main Types of Bonds

The primary types of bonds are defined by their issuers, including the following:

- Government bonds [27]: debt securities issued by a government to support its spending and obligations. These bonds, issued by national governments, are often considered low-risk investments, since the issuing government backs them. Government bonds issued by a federal government may also be known as sovereign debt.
- Corporate bonds [26]: debt securities issued by a firm and sold to investors. The company gets the capital it needs and in return the investor is paid a pre-established number of interest payments at either a fixed or variable interest rate. When the bond expires, the payments cease and the original investment is returned. The backing for the bond is generally the ability of the company to repay, which depends on its prospects for future revenues and profitability. In some cases, the company's physical assets may be used as collateral.

- Municipal bonds [29]: they are debt securities issued by local, county, and state governments, often used to fund capital expenditures like the construction of highways, bridges, or schools. Similar to loans, bondholders become creditors and receive interest on their principal balance, which is repaid by the maturity date. Municipal bonds are often tax-exempt, making them attractive to high-income tax bracket investors.

- Mortgage bonds [28]: they are debt securities secured by a mortgage or a pool of mortgages, usually backed by real estate holdings and property, such as equipment. In case of default, mortgage bondholders can sell the underlying property to compensate for the default. Compared to corporate bonds, mortgage bonds are considered safer and typically have lower rates of return.

A.2. Risks Related to Bonds

Bonds are financial instruments that are subject to a variety of risks that can impact their value and returns [10], [11]. The main financial risks related to a bond include:

- Credit Risk.
  This is the risk that the issuer of the bond will default on its payment obligations. Credit risk is determined by the creditworthiness of the issuer, which is typically evaluated by credit rating agencies. A higher credit rating indicates lower credit risk, while a lower credit rating indicates higher credit risk (see next section for more details).

- Interest Rate Risk.
  This is the risk that changes in interest rates will impact the value of the bond. When interest rates rise, the value of existing bonds with lower coupon rates decreases, making them less attractive to investors. Conversely, when interest rates fall, the value of existing bonds with higher coupon rates increases, making them more attractive to investors.

- Liquidity Risk.
  This is the risk that an investor may not be able to sell the bond at a fair price when they want to sell. Some bonds may have limited trading volumes, which can make it difficult to find a buyer when an investor wants to sell.

- Inflation Risk.
  This is the risk that the purchasing power of the bond's cash flows will be eroded by inflation over time. If the inflation rate exceeds the yield on the bond, the value

of the bond's cash flows will decline, reducing the value of the bond to investors.

- Currency Risk.
  This is the risk that changes in exchange rates will impact the value of the bond for foreign investors. If the value of the foreign currency declines relative to the investor's home currency, the value of the bond will decline as well.

- Country Risk.
  This is the risk that links a bond to the riskiness of the country to which its issuer belongs. Nations, in fact, are also ranked according to their creditworthiness by rating agencies, just as are corporations.

A.3. Credit Ratings

Bonds are evaluated by popular rating agencies, such as Standard and Poor's, Moody's and Fitch. Although each agency has slightly different rating scales, the highest rating is typically AAA, and the lowest rating is C or D, depending on the agency. The top four ratings are regarded as safe or "investment-grade", while anything below BBB for S&P and Baa3 for Moody's is considered "high yield" or "junk" bonds.

Generally, governments have higher credit ratings than companies, and hence government debts are less risky and have lower interest rates.

Below are the complete rating scales used by the three most common rating agencies:

Moody's	S&P	Fitch	Description
Aaa	AAA	AAA	Highest credit quality, minimum credit risk
Aa1, Aa2, Aa3	AA+, AA, AA-	AA+, AA, AA-	Very high credit quality, very low credit risk
A1, A2, A3	A+, A, A-	A+, A, A-	High credit quality (upper-medium grade)
Baa1, Baa2, Baa3	BBB+, BBB, BBB-	BBB+, BBB, BBB-	Good credit quality, currently low credit risk
Ba1, Ba2, Ba3	BB+, BB, BB-	BB+, BB, BB-	Speculative elements, issuer faces major uncertainties and adverse conditions
B1, B2, B3	B+, B, B-	B+, B, B-	High credit risk, but issuer still able to meet its financial commitments
Caa1, Caa2, Caa3	CCC+, CCC, CCC-	CCC	Issuer currently vulnerable, default likely
Ca	CC	CC	Issuer currently highly vulnerable, near default
C	R, SD, D	C, RD, D	Lowest rating, typically in default on some (SD, RD) or all of its financial obligations

An important note, so as not to cause confusion: the rating of a bond refers to the credit rating assigned to the specific bond by a credit rating agency, whereas the rating of an issuer refers to the credit rating assigned to the overall creditworthiness of the issuer of the bond.

While the credit rating of a bond is based on the creditworthiness of the issuer, it also takes into account the specific characteristics of the bond, such as its maturity, coupon rate, and other terms and conditions. Therefore, the rating of a bond may differ from the rating of its issuer.

For example, an issuer may have a high credit rating due to its strong financial position and track record of meeting its payment obligations, but the specific bond may have a lower rating due to its longer maturity or higher coupon rate, which may make it riskier than other bonds issued by the same issuer. Conversely, an issuer with a lower credit rating may issue a bond with a higher rating due to its lower risk characteristics.

In general, the credit rating of a bond is an important consideration for investors when evaluating the risk of investing in the bond, while the credit rating of the issuer is a broader measure of its overall creditworthiness. However, it is important to note that credit ratings are just one of many factors to consider when evaluating the credit risk of a bond or issuer, and investors should conduct their own research and analysis before making any investment decisions.

A.4. Bonds' Price

Bonds are typically issued at a face value or par of 100 EUR per bond. However, once bonds hit the open market, their asking price may differ from their face value, with a lower price referred to as a discount and a higher price as a premium. If a bond is priced at a premium, the investor receives a lower coupon yield due to the higher price, whereas if it's priced at a discount, the investor receives a higher coupon yield due to the lower price.

The price of a bond is determined by discounting expected cash flows to the present using a discount rate. Bonds are issued with a set face value, and they can trade at par, premium, or discount. The current price of a bond depends on its yield to maturity. When the yield to maturity is greater than the coupon rate, the bond is sold at a discount. When the yield to maturity is less than the coupon rate, the bond is sold at a premium. In either case, the bond's current price reflects the present value of its expected cash flows.

Let F be the face value, C be the coupon payment, r be the discount rate, T be the number of periods until maturity, and n be the number of coupon payments per year. Then, the price P of a generic coupon bond can be evaluated as:

$$P = \frac{C}{1+r/n} + \frac{C}{(1+r/n)^2} + \cdots + \frac{C}{(1+r/n)^{nT}} + \frac{F}{(1+r/n)^{nT}} = \sum_{t=1}^{nT} \frac{C}{(1+r/n)^t} + \frac{F}{(1+r/n)^{nT}}$$

The first term of the equation represents the present value of all the coupon payments, while the second term represents the present value of the face value.

Note that this formula assumes that the coupon payments are made at regular intervals, typically semi-annually or annually, and that the bondholder holds the bond until maturity. Additionally, this formula assumes that the bond has a fixed interest rate throughout its life, and that the bond issuer is creditworthy and will not default. If any of these assumptions are violated, the actual price of the bond may differ from the calculated price.

Supply and demand, credit quality, and term to maturity are the three primary influences on bond pricing on the open market. As with all assets, supply and demand play a critical role in determining bond prices. High-yield bonds usually have lower prices to reflect their higher risks, and low-yield bonds usually have higher prices to reflect their lower risks.

The age of a bond relative to its maturity also significantly affects pricing. When a bond matures, it is typically paid in full, although some bonds may be called or defaulted on. As the maturity date approaches, the bond's price moves toward par, reflecting the bondholder's increasing likelihood of receiving the face value. In a "normal" yield curve, bonds with longer terms to maturity have higher interest rates and lower prices due to the increased interest rate and default risks associated with longer-term bonds.

The credit quality of the bond issuer is another significant factor that influences bond prices during and after bond issuance. Firms with lower credit quality will typically have to pay higher interest rates to compensate investors for accepting higher default risk. A decrease in creditworthiness will also cause a decline in the bond price on the secondary market. Bond ratings provide investors with a measure of credit quality and act as signals regarding the creditworthiness and safety of the bonds. Poorly rated bonds have a lower chance of repayment by the issuer, leading to lower bond prices.

A.5. Bonds' Z-Spread

The Z-spread is a financial metric that measures the difference between the yield of a fixed-income security and the yield of a benchmark security. It represents the spread over the benchmark that investors require in order to invest in a particular bond.

More specifically, the Z-spread is the constant spread, measured as a number of basis points (1 bp = 0.01%), that must be added to the spot rate curve [1] so that the present value of the bond's cash flows equals its market price.

In other words, the Z-spread reflects the credit risk of a bond issuer and the risk of the bond's cash flows, as well as any other factors that may affect the bond's yield relative to the benchmark yield. A higher Z-spread indicates that the bond is riskier, and investors require a higher yield to compensate for that risk.

The Z-spread is calculated from this formula: $P = \sum_{t=1}^{T} \frac{C_t}{(1+s_t+z)^t} + \frac{F}{(1+s_t+z)^T}$

where:

- P is the price of the bond;
- F is the face value (or principal) of the bond;
- t is the time (in years) from the present to the payment of the coupon;
- T is the time (in years) from the present to the maturity of the bond;
- C_t is the bond's coupon payment at date t;
- s_t is the spot rate for the specific maturity t;
- Z is the Z-spread of the bond.

[1]The spot rate, for a given maturity, represents the yield on a fixed-income security with that exact maturity. The spot rate curve is created by plotting the yields of fixed-income securities with different maturities against their respective maturity dates.
Spot rates are determined in the market through a process called "bootstrapping", which involves using the yields of fixed-income securities of different maturities to calculate the yields of fixed-income securities with intermediate maturities. This process is repeated until spot rates for all relevant maturities are determined.
The spot rate curve is an important tool for investors and analysts as it provides a benchmark for pricing other fixed-income securities with similar maturities. Additionally, changes in the shape of the curve over time can provide insight into market expectations for future interest rates and economic conditions for the relevant type or credit quality of fixed-income securities.
Source: [12]

Let us see a numerical example to make things clearer.

Example

Suppose we have a bond with a face value of 100€, a maturity of 5 years, and annual coupon payments of 6€. The current market price of the bond is 95€.

The spot rates for bonds of similar credit quality and maturity are as follows:

- 1-year spot rate: 1%
- 2-year spot rate: 2%
- 3-year spot rate: 3%
- 4-year spot rate: 4%
- 5-year spot rate: 5%

Using the formula above, we can calculate the Z-spread for this bond:

$$95 = \frac{6}{1 + z + 0.01} + \frac{6}{(1 + z + 0.02)^2} + \frac{6}{(1 + z + 0.03)^3} + \frac{6}{(1 + z + 0.04)^4} + \frac{106}{(1 + z + 0.05)^5}$$

Using numerical methods, we can solve for z, which gives us:

$$z \simeq 2.52\%$$

This means that investors require a spread of 2.52% above the risk-free rate (represented by the spot rates) to compensate for the credit risk of this bond.

□

The Z-spread can be used to compare the relative value of different bonds with similar credit ratings and maturities.
It can also be used to analyze changes in the credit risk of a bond issuer over time, since they can affect the Z-spread of their bonds. For example, if the creditworthiness of a bond issuer deteriorates, investors may require a higher yield to compensate for the increased risk of default; this would cause the Z-spread of the issuer's bonds to increase.
Conversely, if the creditworthiness of a bond issuer improves, investors may be willing to accept a lower yield, which would cause the Z-spread of the issuer's bonds to decrease.

The Z-spread is a useful tool for financial analysts, as it provides a more comprehensive valuation of a security than a single-point metric, such as a bond's maturity date.
By tracking changes in the Z-spread over time, investors can gain insights into the creditworthiness of a bond issuer and assess whether the issuer's credit risk is improving or deteriorating. Indeed, assuming that the bond's country risk, liquidity risk, and interest rate risk are negligible, the Z-spread can be a reliable indicator of the bond's credit risk. This is because the Z-spread reflects the market's perception of the issuer's creditworthiness based on factors such as its financial health and business prospects.

List of Figures

List of Tables

Ringraziamenti

Con questa tesi magistrale concludo il mio percorso di studi, che in 18 anni della mia vita mi ha portato a diventare un ingegnere finanziario. Un viaggio impegnativo, pieno di ostacoli e criticità, che mi ha permesso di spingermi costantemente oltre i miei limiti e, di conseguenza, mi ha fatto crescere giorno dopo giorno.
Per questo, il primo ringraziamento va a me stesso, per il coraggio che ho messo nel cimentarmi in sfide spesso più grandi di me e per l'abilità ad adattarsi ad esse, uscendone alle volte vincitore ed altre volte ridimensionato, ma mai sconfitto.

Dedico un grande grazie al professor Nassigh, grazie al quale ho avuto la possibilità di svolgere lo stage da cui è poi nato questo lavoro di tesi. Grazie al suo supporto costante, la sua passione per la ricerca e le sue idee brillanti, lavorare insieme a lui è stato per me entusiasmante e stimolante.
Ringrazio anche il professor Marazzina, che si è gentilmente prestato ad essere il supervisore della mia tesi e, soprattutto, è stata una figura di riferimento per il mio percorso di studi, grazie a cui mi sono appassionato al mondo della finanza quantitativa.
Contestualmente, ringrazio tutti i miei professori universitari, in particolare il professor Sgarra, il professor Baviera, il professor Quarteroni, la professoressa Paganoni, il professor Barucci, il professor Gregoratti, il professor Vianello, la professoressa Virgili, il professor Piccardi, il professor Arioli, il professor Potrich, il professor Boella, il professor Verri ed il professor Campi, che sono stati delle grandi fonti di ispirazione e i cui insegnamenti porterò sempre con me.
Un pensiero affettuoso va anche a tutti i miei professori del liceo e delle scuole medie, ed ai maestri delle scuole elementari e dell'asilo. Ciascuno di loro ha contribuito al raggiungimento di questo mio importante traguardo e a rendermi la persona che sono oggi.

Un grazie va anche ai colleghi con i quali ho lavorato durante il mio stage, in particolar modo a Valentina, Luca, Chiara, Matteo, Giorgio e Nicolas. Da loro ho potuto apprendere tanto, sia dal punto di vista professionale che umano, e soprattutto mi hanno sempre messo nelle condizioni di concentrarmi sulla conclusione dei miei studi, pur riuscendo a farmi sentire coinvolto nei processi della Banca e a rendermi partecipe delle loro attività lavorative.