Master Thesis U.S.E

Is news sentiment well suited to predict fluctuations in U.S corporate green bond returns? A comparative study of news and market-based sentiment indicators.[1]

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Abstract. This thesis explores the relationship between news-based and market-based investor sentiment and the returns on corporate green bonds, focusing specifically on the S&P 500 firms. The study tests two hypotheses: (1) Market and news-based sentiment indicators positively predict fluctuations in corporate green bond returns; and (2) Market-based sentiment more accurately predicts these fluctuations compared to news-based sentiment. Using the S&P 500 Green Bond Index as the benchmark, three sentiment indicators are evaluated for their effectiveness in forecasting green bond returns. Despite mainstream literature indicating otherwise, the employed Ordinary Least Squares (OLS) regression models indicate a statistically insignificant relationship between green bond returns and all of the sentiment indicators.News-based sentiment indicators provided a marginally more consistent and stable prediction over the studied period from 2014 to 2024. This research contributes to the temporal understanding of how investor sentiment impacts green bond returns, among else highlighting the importance of robust and representative data.

Key Words. Investor Sentiment, Green Bond, Sentiment Indicator

JEL Codes. G14, G19

1. Introduction

Though historically dominated by supranational organizations, the green bond market has seen periods of substantial growth. According to the Climate bonds initiative (2024), 2021 saw the EU and the U.S issue more than 800 million USD worth of Green Bonds. This decreased somewhat in the following years, partially due to the increase in international tensions. The global cumulative green bond issuance has reached over USD 3 trillion, and Morgan Stanley even refers to this evolution as the *green bond boom* (Flammer, 2021). Green bonds are defined as *"… any type of bond instrument where the proceeds will be exclusively applied to finance or re-finance, in part or in full, new and/or existing eligible green projects and which are aligned with the four core components of the Green Bond Principles (GBP), namely, the use of proceeds, the process for project evaluation and selection, the management of proceeds, and reporting"* (Green Bond Principles, 2021). Green bonds can be issued by anyone from private companies to government agencies or large international organizations. This paper distinguishes between corporate (issued by firms) and sovereign (issued by governments) green bonds, however other types of green bonds do exist (e.g. Municipal) (Flammer, 2021). Even though it was not always the case, the integration and sale of green bonds today can be seen worldwide (Pham and Cepni, 2022). In fact, green bonds are one of the most influential financial tools in the relatively new sphere of *impact investing* (Flammer, 2021). Impact investing can be understood as describing a new set of financial instruments that are catered not only for financial return, but importantly also for environmental impact (Barber et al, 2021; Flammer, 2021; Geczy et al., 2021). For example, Green corporate bonds now account for almost 6% of global corporate bonds outstanding, as opposed to the 1% in 2014 (Caramichael & Rapp, 2024). The world's first green bond was issued by the European Investment Bank (EIB) in June of 2007 (Piñeiro-Chousa et al., 2021; Tang & Zhang, 2018). They called it the *Climate Awareness Bond* (CAB), which provided novel clarity and accountability through the dedicated use of proceeds (EIB, 2022). The first green sovereign bond was issued in Poland followed by France in 2016 and 2017 respectively (Tang & Zhang, 2018). Malaysia on the other hand, is credited to have issued the world's first green Islamic bond, the *green Sukuk*, to finance climate resilient growth in 2017 (Tang & Zhang, 2018). The EIB is credited to play a foundational role in helping establish green bonds as a legitimate asset class, mainly through the scale of CAB issuance and market standards (EIB, 2022). 2007 was also the year of the first AAA-rated green bond, and the first corporate green bond was issued in 2013 (Piñeiro-Chousa et al., 2021). The original and preserved role of green bonds is to aid combat the adverse effects of climate change. However, according to Climate Bonds Initiative (CBI) estimates, for green bonds to have a significant impact on climate targets set by the Paris Climate Agreement (2015), the green bond market ought to have breached 1 trillion USD by 2020. According to the data from CBI, green bond issuance plateaued somewhat after 2019, with 2020 yielding $300 billion in green bond issuance, which is far below the $1 trillion goal. The issuance was much higher in 2021, reaching over $550 billion and receding only somewhat in 2022, achieving almost $500 billion. The first quarter of 2024 on the other hand, was a record-breaking quarter, with almost $200 billion of Green Bonds issued (CBI, 2024). The Paris Climate Agreement was not only one of the most famous climate pacts of its time but also the first legally binding international treaty on climate change (A successor of the Kyoto Protocol (1997) & Marrakech Accords (2001)). According to the United Nations (UN), 2015 was a landmark year, with multiple major international agreements adopted. All 196 UN member countries agreed not only to reduce greenhouse gas (GHG) emissions by 43% by 2030, but also committed to the new *2030 Agenda for Sustainable Development*[2]. At

[2] after the UN Sustainable Development Summit in New York

the heart of this agenda are the 17 so-called Sustainable Development Goals (SDG's) which provide a shared blueprint for human and planetary prosperity. The SDG's build on decades of prior work among the UN members, concerning themselves with global poverty, health, education, inequality and among others, also fighting climate change and promoting the preservation of nature. Though work has been going on for decades, the Paris Climate Agreement became the beacon of multilateral communication and collaboration in the fight against climate change, as for the first-time nations stood united. The Agreement builds partially on the *Copenhagen Accord* (2009) where financial markets were cemented as having a central role in the fight against climate change through the mobilization of private investments for mitigation or adaptation projects (Piñeiro-Chousa et al., 2021). This central role very much remained and is not uncommon practice, for example, the European Commission introduced the so-called *European Green Deal* in 2019. This deal legally commits all 27 EU member states under EU Climate Law, to actively engage in transforming Europe into the first climate-neutral continent in the world by 2050 (EC, 2019). Reboredo (2018) indicates that though climate risks are recognized as a global issue, green bonds are mainly issued in EUR and USD denominated currencies covering approximately 80% of total green bonds issued[3].

For a corporate green bond, or any green bond for that matter, to be certified as *green*, it must undergo third-party verification to establish that the proceeds are used for projects generating environmental benefits (Flammer, 2021). According to Piñeiro-Chousa et al., (2021), green bonds can be considered the main example of an innovative fixed-income investment product that could gather enough capital to finance the fight against climate change. This is also what makes them desirable for a wide range of investors who have environmental strategies or are socially conscious.

[3] Nowadays also China is among the leaders in Green Bond issuance (CBI, 2024)

The rise in green assets and green bonds is a global trend, that follows an increase in corporate focus towards building a "green image", which can often translate into real value for firms (Piñeiro-Chousa et al., 2021). This also provides room for many investors who hope to profit from consumers willing to pay a premium for certified green products or business practices. Piñeiro-Chousa et al., (2021) also discuss a strain of literature that focuses on the yield differential between green and conventional bonds. Literature commonly refers to this as the green bond premium, or the *greenium* (Piñeiro-Chousa et al., 2021; Gianfrate and Peri, 2019). The most common explanation for the greenium is that disclosure and reporting requirements are often associated with additional costs for the issuers of Green Bonds (Fatica et al., 2021). However, an alternative explanation would simply be that the high demand for green bonds creates a mismatch between supply and demand (Piñeiro-Chousa et al., 2021). Recently, Caramichael & Rapp (2024) find on average a 3-8 basis point (bp) lower borrowing cost for corporate green bonds as opposed to regular corporate bonds. This is in line with Zerbib (2019) who also shows a significant negative premium for green bonds compared to conventional bonds. It seems that while green bond governance and external review matter for the greenium, the relevance and credibility of the underyling projects do not (Caramichael & Rapp, 2024). Though empirically seen since 2019, the greenium seems to favor large investment-grade issuers[4], which has implications for the real role that green bonds play in globally incentivizing useful green investments (Caramichael & Rapp, 2024).

Globally recognized brands have unsurprisingly not shied away from issuing green bonds either. In 2014, Toyota issued the largest corporate green bond (at the time) valued at $1.75 billion (Moodie, 2016). In the same year, Unilever issued a £250 million green bond to reduce GHG emissions from existing factories, and in 2017, Apple issued a $1 billion green bond to finance

[4] mostly in developed economies and the banking sector (Caramichael & Rapp, 2024)

sustainable practices at its facilities and in its supply chain (Flammer, 2021). Compared to the global bond market, the green bond market is relatively small, however over time this discrepancy is predicted to shrink (Piñeiro-Chousa, 2021).

In all the time that financial markets have operated, there have been many notable instances of panic, crashes or simply mania that are difficult to explain using economic fundamentals alone (Zhou, 2018). An event where a dramatic change in the level or prices seems to defy explanation is defined as mania or crash (Baker & Wurgler, 2007). Some notable examples include the Great Crash of 1929, the Black Monday Crash of October 1987, the Internet or Dot.com bubble of the 1990's and the Financial Crisis in 2007-08 (Baker & Wurgler, 2007; Zhou, 2018). Historically standard financial models, which often used rational investors and efficient markets as their assumptions, had a very hard time accommodating these price patterns (Baker & Wurgler, 2007). Therefore, researchers in behavioral finance tried to augment the standard models, by including two basic yet important assumptions. The first being that investors are in fact influenced by sentiment, where sentiment is simply defined as the belief about future cash flows or investment risks that is not justified by the facts available (Baker & Wurgler, 2007). The second assumption is that betting against sentimental investors is costly and risky. Empirical evidence at the time pointed towards rational investors (or Arbitrageurs) not being as aggressive in forcing prices back to their fundamental value as the standard models would like to suggest (Baker & Wurgler, 2007). The first assumption was described by De Long et al., in 1990 and the second assumption was commented on by Shleifer and Vishny in 1997 (Baker & Wurgler, 2007).

The paper by De Long et al. in 1990 is regarded as one of the first influential papers to contribute to the concept commonly referred to as *Investor Sentiment*. They managed to show that the unpredictability of noise traders' beliefs (*noisy trading risk*) can be responsible for asset prices diverging from their fundamental value (Zhou, 2018). This is strange, because it happens even in the absence of fundamental risk. Since the introduction of Investor Sentiment, several models have been developed to help clarify how sentiment evolves and impacts the financial markets. Due to the inability to directly observe sentiment, it essentially depends on how accurately we can estimate it in the market. Initially the best indicator was the closed-end fund discount[5], but more recently indexes comprised of multiple indicators have been used (Zhou, 2018). One of the most famous such indexes formed was the Baker & Wurgler (BW) (2006) investor sentiment index which incorporates 6 indicators including the closed-end fund discount (Zhou, 2018). This index was influential because it was able to capture investor sentiment much better than any one of its indicators could alone. This was initially described for the movement of stocks; however, sentiment and bonds seem to work in a similar way as sentiment and stocks do (D'Hondt & Roger, 2018; De Long et al., 1990). Today, we recognize multiple sources from which academia extracts investor sentiment. Historically most sentiment indexes were commonly based on market data (Baker & Wurgler, 2006; Brown & Cliff, 2005; De Long et al., 1990), however over time survey data emerged and recently more academics have also been using text and media data (Zhou, 2018; Dong & Gil-Bazo, 2020; Piñeiro-Chousa et al., 2021). The use of investor sentiment indexes and the major trends in literature will be discussed further in-text.

Sentiment being an intangible concept, it requires a broader scope to be explored in a quantitative sense. Better said, it requires an understanding of consumer human rationale and consumer (or investor) decision-making. Almost two decades ago, Baker and Wurgler (2007) discuss how psychological factors significantly contribute to the understanding of investor behavior. They challenged the notion that investors behave rationally and that markets are perfectly efficient.

[5] as explained by Lee, Shleifer & Thaler (1991)

According to Baker and Wurgler (2007), emotions and cognitive biases play a critical role in the functioning of financial markets. This is in-line with the development of behavioral finance, which is focused on integrating insights from psychology into economic models. This integration helps better explain market anomalies otherwise unjustified by traditional theories. Some commonly discussed biases include overconfidence, herd behavior or risk aversion (Baker & Wurgler, 2007). If common enough in the market, these biases can influence market trends or cause sentiment-driven mispricings (López-Cabarcos et al., 2017; Brown & Cliff, 2005). For Green bonds, we commonly witness the *greenium*, which is simply a green bond priced away from its fundamental value. If the greenium is in fact caused by the investors belief, then this kind of relationship should be reflected in the *mood* of the green bond market as well (Caramichael & Rapp, 2024). This relationship can be captured through investor sentiment, and help fully comprehend the dynamics of the market (Piñeiro-Chousa et al., 2021; Caramichael & Rapp, 2024).

Whether the rising demand for green assets is a temporary trend, or a real response to imminent danger will likely be long debated between ideologically diverse groups (Piñeiro-Chousa, 2021). The consensus among researchers seems to be that green bonds are the result of an increase in environmental risks and concerns (Piñeiro-Chousa et al., 2021). Following this train of thought, it is easy to believe that the demand for green bonds will continue to increase. With rising investments in green bonds, the more key it becomes to understand how green bonds and financial markets co-move. Reboredo (2018) argues to this point that this is important information for many interested parties (Investors, Researchers, Policy makers…etc.), as it highlights important relationships. Good examples would include (but are not limited to): the diversification benefit of allocating green bonds into portfolios or the impact of price fluctuations (in the financial market) on green bond prices (Reboredo, 2018). Pham and Huynh (2020) also discreetly underline the importance of green bonds as an environmentally oriented financial instrument. They highlight two important points, the first being that empirical evidence highlights how the green bond market is correlated with the fixed-income currency markets (Reboredo & Ugolini, 2020; Tang & Zhang, 2018), even though it is weakly correlated to stock, energy and high-yield corporate bond markets (Pham & Huynh, 2020). Therefore, offering some diversification benefits for their investors. Secondly, with concerns over climate change ever present, more investors search for explicitly environmentally friendly investments (Pham & Huynh, 2020). Put together, understanding the complex interdependencies between investor sentiment and the green bond market can promote more adequate implementations of policy for green finance (Pham & Huynh, 2020).

The extension of current literature and focus of this paper will be the following. One market-based sentiment indicator will be used in a model with Green Bond returns. This model will be placed against two sentiment indicators[6] constructed and based on news articles respectively. I hope to see whether news sentiment can be plausibly used to proxy investor sentiment for corporate green bond returns as well as other (market based) sentiment indicators can. I will focus on the S&P 500 firms because most green bonds are still issued by large brands, and the S&P 500 provides a great index to work on. Therefore, I consider corporate bonds, or ones issued by firms. It is important to understand how and to what extent our knowledge of bond markets can be applied as is, when considering the complex and novel workings of the green bond market. Seeing that green bonds are a response to a globally acknowledged climate trend, it is not unwise to assume that news sentiment could potentially prove useful in predicting investors' green bond sentiment (Dong &

[6] Using the same base model

Gil-Bazo, 2020; Piñeiro-Chousa et al., 2021). For the purposes of this paper the research question (RQ) is as follows:

RQ: *Is news sentiment better suited to predict fluctuations in U.S corporate green bond returns?*

1. Literature Review

In 2002, Daniel Kahneman, an American psychologist, received the Nobel Prize in economics for his work illuminating the role psychology plays in the decisions economic agents make under uncertainty (KVA, 2002). Influential works such as these showcase the importance of understanding the complex nature of interdisciplinary relationships. In Kahneman's case, the result was the role of psychology being cemented into our core understanding of economic rationale (Phuong and Nhung, 2021). More recently, Phuong and Nhung (2021) indicate that psychology can possibly provide an additional perspective in explaining stock price changes in the stock market other than the traditional Fama's 1970 efficient market hypothesis (EMH) and standard asset pricing models. The efficient market hypothesis, as presented by Eugene Fama (1970), conveys a simple idea that it should be impossible to consistently outperform the market. In other words, if anyone could consistently outperform the market, then everyone would, and soon it would not yield any above-market results. Fama believed that all publicly available stock information must be reflected in the price of the stock, one reason for this belief was the vast volume of trades occurring in the market. He made the distinction between 3 types of the EMH, namely: *Weak form*, *Semi strong* form and *Strong form* EMH (Fama, 2017). According to Fama (2017), *Weak form* market efficiency describes the situation in which current market prices reflect historical information (i.e. prices). *Semi strong form* extends this notion to include all publicly available information at the time. Lastly, the *Strong form* goes even further to assume that accessed insider (Monopolistic) information is reflected in the market. All these forms reflect an instance of an efficient market (Fama, 2017). If markets are efficient then the simple conclusion is that if stocks trade at a fair value, it is impossible to arbitrage them consistently for abnormal profits (thus outperforming the market as well). Even though this relationship seemed to hold, there are documented instances where prices fluctuate away from their fundamental values. One great example is the premium for green bonds, or in other words, the greenium. Fama, according to his EMH, would only attribute the outperformance to blind luck, but this seems far from reality as the trend is visible over long periods of time. Furthermore, alternative views on the EMH point out there are times of high pessimism or optimism, which correspond to the prices of stocks or bonds to be respectively underpriced or overpriced, which goes directly against the conclusions of the EMH.

2.1 Investor Sentiment

This type of mispricing based on excessive optimism or pessimism known as *investor sentiment* was visited by Baker and Wurgler (2006), who defined it as mentioned above: "*a belief about future cash flows and investment risks that is not justified by the facts at hand*". There were pioneering studies conducted already in the 1980's on sentiment and bond returns, however the role of sentiment was implicit and the empirical evidence far from strong (Baker and Wurgler, 2007). This resulted in weak statistical inferences or ones with limited economic interpretation (Baker and Wurgler, 2007). Studies in the early 2000's therefore quickly adopted novel methods to estimate the effects of sentiment (Piñeiro-Chousa et al., 2021). Most of the time the advances came from behavioral finance theory, however the roots can be traced to the 1990's behavioral models by DeLong, Shleifer, Summers and Waldmann (Baker and Wurgler, 2007). They describe the basic setup for investor sentiment, which distinguishes between two types of investors. The so-called *rational arbitrageurs,* who are sentiment-free, and the *irrational traders* who can be prone to exogenous sentiment (Baker and Wurgler, 2007).

Rational arbitrageurs are also further limited compared to irrational traders, as they have much shorter time horizons and stricter trading constraints – also known as *Short Sale Constraints* (Baker and Wurgler, 2007). Due to the nature of rational arbitrageurs, prices are not always considered as part of their fundamental values, as they are mostly focused on arbitrage opportunities. The two types of investors naturally differ and compete in the market to set the prices. Mispricing arising from both investor types can be modelled out of two factors: *arbitrage restrictions for rational investors* and a *change in sentiment for irrational investors* (Baker and Wurgler, 2007). With respect to the second factor, which can also be called the *uninformed demand shock*, Brown and Cliff (2005) point to sentiment being a very persistent effect, which can cause consecutive demand shocks of uninformed noise traders to correlate over long periods of time. This can ultimately cause persistent mispricings. Additionally, if mass groups of irrational sentiment investors (the second factor) trade in unison, they may generate a sizeable proportion of total trading. This in turn increases the risk and cost for rational arbitrageurs to bet against them (Shleifer and Vishny, 1997), because it is unclear how persistent the overall sentiment pressure in the market will remain. Theory and empirical data however also show that mispricings are eventually always corrected, so it is common to see periods of high/positive optimism/sentiment followed by periods of consistent low returns, and vice versa (Schmeling, 2009).

Because it is impossible to measure investor sentiment directly, the construction of the most appropriate sentiment indicator has been a topic amongst academics for decades. In 1991, Lee et al., first used the discount rate of closed-end funds as an indicator, however studies have since proposed three main categories for investor sentiment proxies[7].

The first category comprises of subjective indicators created through investigation (e.g. Surveys), an example is the American Association of Individual Investors (AAII). It is good to note here that though sentiment indicators can directly reflect investors' psychological predispositions, the resulting transactions made by said investors might not consistently reflect expectations.

The second type of sentiment indicators are objective indicators, which are constructed from transaction data (for instance mutual fund flows). These can indirectly reflect investor sentiment (Frazzini and Lamont, 2008). Sentiment is a complex concept, one indicator is usually not enough to fully grasp the effect, therefore a composite investor sentiment index combining various indicators is necessary (Gao et al., 2022). Baker and Wurgler (2006) made the BW index (constructed using principal component analysis – PCA) which uses 6 different market trading indicators to reflect market sentiment. They include the *closed-end fund discount rate*, *turnover rate*, *initial public offering (IPO) number*, *IPO first-day earnings*, *share ratio* in newly issued bonds and stocks, and the *dividend premium*. It is also important to note that market sentiment indicators do not reflect the sentiment of specific stocks, for that a more specific metric should be used.

The third and last kind of investor sentiment indicators as described by Gao et al. (2022) are internet/media indicators (e.g. News). With vast amounts of data online becoming more accessible,

[7] As described by Gao et al. (2022)

often complex machine learning methods are tailored to search for trends online. One of the first papers to fully utilize the potential of this method was Antweiler and Frank (2004), who using investor postings on Yahoo finance, applied the naïve Bayes method to classify text sentiment.

Additional sentiment indicators include technical analysis indicators that showcase investor sentiment daily. One such indicator could be the commonly used CBOE implied volatility index (VIX), which uses real time data to average the weighted prices of puts and calls over a wide range of strike prices. It's then possible to imply the expected market volatility, and infer the predicted movement in, for example, the S&P 500 index. Other studies, however, combine separate indicators into a general sentiment indicator. One such paper was written by Phuong and Nhung (2021), where a general sentiment variable was used, measured by first component extraction when applying PCA to individual technical analysis indicators (Relative Strength Index, Psychological Line Index). The results indicated that investor sentiment positively influences stock returns, meaning that higher sentiment likely increases stock returns, ceteris paribus. This result was significant even when controlling for factors such as firm size, cash flow per share, CAPM beta and even stock price volatility (Phuong and Nhung, 2021). Similarly, Borovkova and Zhang (2022) note that they find a statistically significant negative relationship between news sentiment and bond yields. With bond yields and returns having an inverse relationship, we can infer a positive relationship between news sentiment and bond returns. However, this relationship seems to be asymmetric, with a decrease in sentiment having a larger impact on bond returns than an increase (Borovkova & Zhang, 2022).

2.2 Background literature on Green Bonds

The Paris Agreement (2015) was a big step towards a global effort to mitigate the effects of climate change (UNCC, 2021). However, global financial efforts to combat the adverse effects of climate change began decades before then through the (at the time) influential concept of Corporate Social Responsibility (CSR) (Jamali & Mirshak, 2006). CSR stems from the global need for transparency in business, as governments are no longer able (or eligible) to provide all goods and services for their population (Jamali & Mirshak, 2006). Progressive companies promote the role of business in society through engagement in CSR. The concept promotes maximizing the positive impact of company operations on society (Jamali & Mirshak, 2006). However, nowadays we talk mostly in the plane of Environmental, Social and Governance (ESG) metrics in finance, as they have gained major traction in the last decade (Halbritter & Dorfleitner, 2015). ESG metrics (score or performance) rate the sustainable practices and environmental impact of a business. They can act as a proxy to indicate how environmentally aligned a company is (Halbritter & Dorfleitner, 2015).

Indicators such as CSR or ESG serve a valuable purpose, but they are not enough to make an (environmentally) tangible difference. To this accord, several major economies managed to agree on the best approach to increase current investments (Piñeiro-Chousa et al., 2021). These investments were primarily to aid in preventionary, and transitional[8] measures targeted at mitigating the adverse effects of climate change. The consensus was to create and promote financial products catered to the tastes of investors with a substantial asset base (Piñeiro-Chousa et al., 2021). Green bonds, seemingly perfect for the occasion, are a good example of an innovative

[8] Transitional towards more sustainable or environmentally friendly products and practices (Piñeiro-Chousa et al., 2021)

fixed-income investment product, that can attract large amounts of capital to finance the battle against climate change (Piñeiro-Chousa et al., 2021).

Reichelt (2010), defines green bonds in the Euromoney Handbook simply as *"... a 'plain vanilla' fixed income product that offers investors the opportunity to participate in the financing of 'green' projects that help mitigate climate change and help countries adapt to the effects of climate change"*. Green bonds are in many ways very similar to regular bonds, for example they include credit risk and size. What does differentiate them is their unique characteristic that any proceeds from the sale of such bonds must be invested in projects with a net positive environmental impact (Reichelt, 2010). A key feature of green bonds is also the due diligence[9] process on the side of the issuer. They are expected (mainly by the bond holders) to continuously identify and monitor currently active or potential projects.

Piñeiro-Chousa et al. (2021) regard green bonds as being extremely effective in battling climate change, mainly due to their standard financial characteristics in tandem with their dedication towards environmental issues. To a large degree this is the reason they grew in popularity so rapidly from 0.6% of all bonds issued in the European Union (EU) in 2014, to 8.9% in 2022. Even though (partially attributable to COVID-19) there has been a significant plateau in the increase in green bond issuance between 2021 - 2023 (EEA, 2023). From the various types of green bonds that can be issued, green corporate bonds have seen one of the most remarkable increases in the recent past. From 4.7% of total corporate bonds issued in 2020, to 11% in 2022. In Europe, these past and predicted future increases in the use of green bonds can be attributed partially to the ambitious environmental and climate objectives of the European Green Deal (EEA, 2023). These inherent

[9] Regulatory Compliance in this case

features of green bonds make them attractive to a wide range of investors. Piñeiro-Chousa et al. (2021) describe investors as including (but not limited to) retail and high net worth investors, institutional investors looking for climate-oriented investments or socially conscious investors with specific climate-related strategies. The growth of national green bond markets has been substantial, however, it depends on different variables. Some important factors according to the EEA (2023) are *policy and regulatory factors*, *market conditions* or *financing trends*. Not only in Europe, but globally, the growth of green bond markets faces several challenges. The EEA (2023) name a few, including *underdeveloped national bond markets*, *insufficient stock of standardized green projects* (ready for funding through green bonds), *lack of universally accepted green bond standards* (and definitions) and lastly a *discrepancy between small-scale projects and large-scale institutional investors*.

Despite the growth in green bond issuance, a challenging aspect for furthering market growth and investor confidence has come to light in past years. Mutarindwa et al., (2024) recommend issuing green bond certifications in response to *greenwashing*, which has become a widespread issue across various green markets. Greenwashing is the practice of making misleading or unsubstantiated claims about a company's commitment to the environment (Flammer, 2021). The internationally recognized voluntary process guidelines, the *Green Bond Principles*, have been used more often in recent years to battle greenwashing and diversify climate risk in financial investment portfolios (Pham and Cepni, 2022). However, the Green Bond Principles are not mandated or enforced, in fact they just promote the role that global debt capital markets have in financing environmental and social sustainability (Piñeiro-Chousa et al., 2021; Green Bond Principles, 2021). Though different certification standards have since emerged and been on the rise, there is no single universally accepted standard for certification (Piñeiro-Chousa et al., 2021).

Over time, however, a more user-friendly and unilateral approach to standardizing green bonds is anticipated. This will also be necessary if the problem of greenwashing worsens in the future.

Due to different aspects of green bond certifications being internationally accepted over time[10], it is natural to expect additional investment to appear alongside these developments. This is achieved mainly indirectly through more readily available market data on green bonds and lower costs for holders and issuers due to economies of scale (Flammer, 2021). And with more investors who bring in more funds, the result is an environment which has seen a dramatic increase in research over time.

Irrespective of the challenges, with annual investments in green bonds on the rise, it is important to understand how investor sentiment translates into this environment (Reboredo, 2018; Broadstock & Cheng, 2019).

Especially with the increasing importance of climate related issues in finance, the role and relationship between news sentiment and green bonds should be analyzed. News sentiment regarding green bonds can also be interpreted as the attitude of the public towards green bonds. Both Reboredo (2018) as well as Reboredo and Ugolini (2020) indicate a link between green bonds and corporate/treasury bond markets. Additionally, Broadstock and Cheng (2019) also indicated a strong linkage between green bond news-based sentiment and green bonds. They indicate that the connection between green and black[11] bonds is sensitive to macroeconomic factors which included among else also news-based sentiment towards green bonds. Ultimately, Piñeiro-Chousa et al., (2021) imply that the relationship between media sentiment and the green bond market has been

[10] Such as a unified definition of green bonds or a standardized set of 3rd party certifications (Flammer, 2021).
[11] Black bonds are understood here as the aggregated US domestic bonds

under researched, and since the news are a proven resource, this relationship should be analyzed in depth (Broadstock & Cheng, 2019).

The lack of research underpinning the influence of investor sentiment on bond markets is the base of this paper, which aims to compare the use of news sentiment indicators[12] in order to determine which is more suitable to reflect fluctuations in green bond returns.

2.3 Hypothesis Development

To address the simplified research question of this paper—whether news sentiment indicators can be as effective as market sentiment indicators in predicting U.S corporate green bond returns—several hypotheses must be formulated to reach a sound conclusion. The significant positive relationship between Investor sentiment and returns on securities including green bonds has been academically documented and well established over the years (Baker & Wurgler, 2007; Pham & Cepni, 2022; Piñeiro-Chousa et al., 2021; Schmeling, 2009; Zerbib, 2019). To test not only the computed news sentiment, but all of the indepent variables described in section 4.2, the following initial hypothesis is formulated:

H1: *Market and News based sentiment Indicators positively predict fluctuations in corporate green bond returns.*

[12] type 3 (News) to type 2 (Market) indicators

Both the market and News sentiment Indicators have been discussed in literature as having their own advantages and drawbacks. This paper focuses on the implementation of News articles as a base for investor sentiment. News articles, being derived from real-time media coverage, can provide immediate insights into market trends or reactions. In this way, news-based sentiment indicators quickly adapt, capturing sudden changes in the market. To this effect, Huang et al. (2019) show that news-based sentiment indicators can provide early warning before a market downturn by capturing nuances market-based indicators might miss. It is important to note here that though news-based sentiment is more agile when the mood in the market shifts, it is also more susceptible to short-term fluctuations that might not reflect fundamental changes in price (Huang et al., 2019).

Market-based sentiment indicators, however, have been commonly used for years, and they have yielded significant results as well (Baker & Wurgler, 2006). These indicators tend to be more stable considering sudden change, which (depending on the nature of the change) can be interpreted as either a positive or a negative virtue. On the one hand they provide a more consistent measure of overall market sentiment, but on the other they are also not able to include immediate market updates. Thus, they provide an inherently lagged reflection of current market conditions (Huang et al., 2019).

Considering that this paper focuses on a 10-year time period from 2014-24, the market-based sentiment indicators should provide more consistent and stable predictions of investor sentiment and long-term market trends. Therefore, the secondary hypothesis of this study is:

H2: *Market-based sentiment will more accurately predict fluctuations in corporate green bond returns compared to News-based sentiment.*

2. Data Collection and Methodology

The purpose of this paper is to provide further insights into how well different sentiment indicators explain fluctuations in green bond returns. The geographic focus is on the U.S market, specifically on the S&P 500 listed firms, because apart from the EU, the U.S is one of the largest issuers of green bonds worldwide (CBI, 2024), and the S&P 500 provides a strong index to test the hypothesis on (Baker & Wurgler, 2006).

4.1 Data Collection

Both financial and news data are collected and used in this paper. All the data used is in daily frequencies. Financial data was collected from various sources, and several indices are used throughout. The *S&P 500 Green Bond Index*, *S&P 500 Bond Index* as well as the *S&P 500 Index* were downloaded through *spglobal* (S&P Dow Jones Indices LLC). The data is from April 2014, until April 2024. There are 2607 daily observations in the datasets. Furthermore, the daily *CBOE Volatility Index* (VIX) was acquired from Yahoo Finance, as a measure to control market volatility. The market-based sentiment indicator used is the International Securities Exchange Sentiment Index (ISEE), downloaded from Nasdaq.

In terms of non-financial data, or data on news sentiment, I downloaded 1647 news articles from NexisUni (LexisNexis) for the period 2014-24. The articles were filtered to pertain to only U.S firms and with respect to green bonds[13]. The data is daily, however not all the days are covered, with most articles being in 2022 (464) and least articles in 2014 (51). The distribution of articles in years can be seen in Appendix I. These articles were then used as the base to construct a sentiment indicator using a natural language processing (NLP) technique in Python. This python library is the FinBERT, which builds on the original vastly successful BERT (Bidirectional Encoder Representations from Transformers). BERT builds on many different natural language processing methods developed and is pre-trained so that limited computing power is necessary to use it (Araci, 2019). FinBERT is a permutation of the classic BERT, which fine-tunes BERT on a corpus of financial text, so that it is more well suited to handle investor sentiment analysis (Genc, 2020). Though FinBERT can evaluate text in a number of ways, for the purposes of this study only the compounded sentiment score is used[14].

Additionally, I obtained the Daily News Sentiment Index, which is a high frequency measure of sentiment based on lexical analysis of news articles. It was first described by Buckman et al. (2020). The index aggregates individual news article scores into a daily time-series measure of sentiment, also including trailing weights that decline geometrically with time since publication (FRBSF, 2023). This index, which is based on a lexicon specifically made for economic news articles, performs better than traditional off-the shelf models by having higher predictive accuracy (Shapiro et al., 2020). I will use it as a baseline to evaluate the FinBERT-constructed sentiment indicator in this study. The index was downloaded from the Federal Reserve Bank of San Francisco (FRBSF).

[13] Searched filter: "Corporate Green Bonds"
[14] This is the average of the Positive, Neutral and Negative

Lastly, due to increase in global tension that affects the U.S markets (e.g. Russo-Ukrainian War, Israel- Hamas War), there is also a Geopolitical Risk Index (GPR) included in the model, to account for the short-term impacts of conflict and international tension (Brune et al., 2011). This is important to include, because although stocks don't always underperform during the times of conflict, bonds can drop below their historical averages during times of war (Armbruster, 2022; Brune et al., 2011). The GPR Index is as described by Caldara and Iacoviello in 2022. The GPR was downloaded from the website of Matteo Iacoviello.

2.2 Variables

The Variables used in this paper are visualized below in Table 1. All the variables used in the regressions apart from time component *year* are expressed in daily log-returns. There are 3 distinct categories of variables, namely: Dependent Variable (DV), Independent Variables (IV) and the Control variables (Controls).

	Full Name	**Variable Name**	**Definition**	**Source**
Dependent Variable	S&P 500 Green Bond Index	GBI	Daily log-returns on the Index	SPGLOBAL
Independent Variables	International Securities Exchange Sentiment Index	ISSE Change	Daily log-returns on the Index	Nasdaq
	FinBERT News Sentiment	FinBERTsent	Daily log-difference of computed news sentiment	NexisUni
	Daily News Sentiment Index	NewsSent	Daily log-returns on the Index	FRBSF

Control Variables	Geopolitical Risk Index	GPR	Daily log-returns on the Index	Matteo Iacoviello
	S&P 500 Index	SPI	Daily log-returns on the Index	SPGLOBAL
	S&P 500 Bond Index	BI	Daily log-returns on the Index	SPGLOBAL
	CBOE Volatility Index (VIX)	Volatility (VIX)	Daily log-returns on the Index	Yahoo Finance

(Table 1: *Variable Descriptions and Source*)

2.3 Ordinary Least Squares

Following the methodology of Dong and Gil-Bazo (2020), adjusted to determine the influence of investor sentiment on corporate green bond returns, I will conduct a time-series analysis using the Ordinary Least Squares Estimator (OLS). To ensure normality in the standard errors log-returns for all variables are used as regression data[15]. Furthermore, all regressions in STATA are run using the *,robust* command to ensure robust standard errors to account for heteroskedasticity of the data[16]. Lastly, the regressions are run using the *i.year* command which ensures fixed time effects as the regression controls for time trends (Bell & Jones, 2015). The model, which is identical across all IV's (models), is as follows:

$$GBI_t = \beta_0 + \beta_1 \Delta sent_{it} + \beta_2 Controls_t + \beta_3 year + \varepsilon_{it} \tag{1}$$

[15] For a more accurate estimation due to abnormal data distribution – see section 5.3.5)
[16] See section 5.3.2

Where GBI_t represents the log returns for the S&P 500 Green Bond Index at time t, $\Delta sent_{it}$ is the log-change in sentiment indicator i at time t. The *Controls* consist of BI_t which is the log-return in the S&P 500 bond Index at time t. SPI_t is the log-return on the S&P 500 Index at time t used to control for the effect of the S&P 500 as a whole. VIX_t is the log-return on the CBOE Volatility Index[17] at time t, and GPR_t is the log-return on the Geopolitical index at time t. Variable *year* provides data on the year to control for seasonality and ε_{it} is the error term for model with sentiment indicator i at time t.

Based on Piñeiro-Chousa et al. (2021), News sentiment *sent* for a given day t is calculated as follows:

$$sent_t = \sum_{i=1}^{n} S_{it} / n_t \tag{2}$$

Where for news sentiment S_{it} is the sentiment of article i at time t (constructed using FinBERT)[18]. And n_t is the number of articles published on day t.

From this the log-change in sentiment for indicator i:

$$\Delta sent_{it} = \ln\left(sent_{it} / sent_{it-1}\right) \tag{3}$$

[17] Measure of market volatility

[18] For the indicators downloaded from the web, equation 2 is omitted as the data is provided directly.

Where $sent_{it}$ (from equation 2) is the value of green bond investor sentiment using sentiment indicator i at time *t*.

After running all OLS estimators using the different investor sentiment indicators, the regression outputs are compared to ascertain which sentiment indicator better predicted the fluctuations in green bond returns.

2.4 Limitations

The most impactful limitation that is clear from the data is the lack of days in the FinBERT sentiment dataset. The sentiment analysis was conducted on all the articles available on any given day, but not all the days in the trading year are covered each year. Due to the regressions using daily observations, missing data creates jumps between days which can influence the daily effect of news sentiment or any other sentiment indicator for that matter (Ahn et al., 2022). Furthermore, the data range also includes the years of the COVID-19 pandemic, which heavily impacted global financial markets, further skewing the data reliability (Wei & Han, 2021). Lastly, the market based and news-based sentiment indicators chosen to proxy investor sentiment might not fully encompass the mood in the Green Bond market. Green Bonds are inherently influenced by various ESG factors, which are likely omitted in traditional sentiment measures (Friede et al., 2015). These are considerations to have in mind before interpreting the results too closely.

5. Empirical Analysis

5.1 Descriptive Statistics

Table 2 provides an overview of the variables used in the following regressions and their characteristics. The variables are presented in percentage log-differences.

Variable	Observations	Mean	Std. Dev	Min	Max
SP500_GreenBond	746	-0.011	0.797	-10.20	4.46
SP500_Bond	746	0.031	0.881	-14.63	11.53
SP500_Index	746	0.123	1.907	-20.99	14.42
Volatility	746	0.032	12.902	-56.70	92.09
GPR_Change	746	11.778	52.252	-188.06	255.09
FinBERTsent	738	0.112	227.255	-1615.228	1610.23
NewsSent	707	0.588	-369.319	-369.32	483.13
ISEE_Change	746	-0.371	-143.988	-143.99	121.64

(Table 2: *Variable Summary Statistics)*

5.2 Regression Analysis

To attempt and answer the hypotheses using 3 different IV's, 3 separate models were constructed. For every model described below, the regression was built up starting from a direct IV on DV relationship[19], and then by continuously adding variables by one, 5 permutations are considered. Both Hypotheses 1 and 2 are evaluated in section 5.2.4.

[19] Sentiment Indicator *i* on green bond returns

5.2.1 International Securities Exchange Sentiment Index (ISSE). Model 1 consists of the market-based sentiment indicator modelled together with the specified controls and green bond returns. The regression results of all 5 permutations (a - e) and their significance levels are listed. The model consists of 746 unique datapoints.

Traditional market-based sentiment Indexes report a positive significant relationship (Baker and Wurgler, 2006; Piñeiro-Chousa et al., 2021), however, in this model this was not the case. Results showcase an insignificant negative relationship across all 5 specifications between ISEE and Green Bond Returns. Contrary to what majority of academic literature reports, no statistically significant relationship has been found between investor sentiment and the returns on Green Bonds. The coefficients are all negative, and very close to 0. Furthermore, we also notice no significant relationship between green bond returns and Geopolitical Risk (GPR), as well as Volatility/ VIX. All coefficients on both controls for the S&P 500 Index and the S&P 500 Bond Index are positive and highly significant at the 1% level. This is unsurprising as they all track the S&P 500 in some way, so they are highly linked (Zerbib, 2019). The insignificant relationship between the S&P 500 Green Bond Index and the ISEE sentiment can also be viewed from the rather small R^2 from model 1a, at only 2.3%. This R^2 increases drastically with the introduction of control variables, which could indicate abnormal multicollinearity (Dormann et al., 2012; O'brien, 2007). The mean VIF (Variance Inflation Factor) around 2.5 for all model specifications does not further substantiate this risk and indicates only low to moderate multicollinearity[20]. More on robustness checks in section 5.3.

[20] VIF > 10 is considered high multicollinearity

Model 1: *ISEE Sentiment Regressions*

VARIABLES	(a) SP500_GreenBond	(b) SP500_GreenBond	(c) SP500_GreenBond	(d) SP500_GreenBond	(e) SP500_GreenBond
ISEE_Change	-0.00140	-3.15e-05	-0.000294	-0.000262	-0.000268
	(0.00126)	(0.000790)	(0.000792)	(0.000790)	(0.000792)
SP500_Bond		0.668***	0.619***	0.603***	0.603***
		(0.0798)	(0.0790)	(0.0808)	(0.0809)
SP500_Index			0.0472***	0.0768***	0.0773***
			(0.0161)	(0.0232)	(0.0233)
Volatility				0.00517	0.00528
				(0.00328)	(0.00330)
GPR_Change					-0.000320
					(0.000328)
2015.year	-0.0101	0.0603	0.0737	0.0828	0.0789
	(0.152)	(0.141)	(0.143)	(0.144)	(0.144)
2016.year	0.138	0.134	0.143	0.150	0.151
	(0.155)	(0.122)	(0.124)	(0.124)	(0.124)
2017.year	0.258**	0.273***	0.276***	0.280***	0.283***
	(0.125)	(0.0985)	(0.100)	(0.102)	(0.102)
2018.year	0.0661	0.167*	0.174*	0.176*	0.180*
	(0.114)	(0.0982)	(0.0988)	(0.101)	(0.101)
2019.year	0.204*	0.144	0.154*	0.162*	0.163*
	(0.112)	(0.0889)	(0.0910)	(0.0932)	(0.0933)
2020.year	0.286	0.260**	0.268**	0.268**	0.267**
	(0.206)	(0.114)	(0.116)	(0.118)	(0.117)
2021.year	0.0699	0.143	0.145	0.149	0.150
	(0.109)	(0.0905)	(0.0920)	(0.0944)	(0.0945)
2022.year	-0.0634	0.0912	0.105	0.117	0.118
	(0.137)	(0.103)	(0.104)	(0.106)	(0.106)
2023.year	0.169	0.221**	0.222**	0.226**	0.228**
	(0.135)	(0.103)	(0.104)	(0.106)	(0.106)
2024.year	0.262*	0.253**	0.262**	0.264**	0.263**
	(0.143)	(0.104)	(0.106)	(0.108)	(0.108)
Constant	-0.116	-0.187**	-0.198**	-0.207**	-0.204**
	(0.102)	(0.0839)	(0.0860)	(0.0881)	(0.0882)
Observations	746	746	746	746	746
R-squared	0.023	0.560	0.570	0.573	0.573
TIME FE	YES	YES	YES	YES	YES
Mean VIF	2.66	2.53	2.46	2.59	2.49

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Seasonality and time trends are also controlled for in this model, with time fixed effects yielding significant positive coefficients[21] for years 2017, 2020, 2023 and 2024. These significant and positive coefficients indicate that the average green bond returns were higher in these years compared to 2014 levels by about 0.25%, ceteris paribus. This could be due to various reasons, one being the COVID-19 pandemic, which increased awareness of social and environmental issues (Wei & Han, 2021). Alternatively, temporal spikes in demand could be the result of policy or larger institutional changes.

5.2.2 FinBERT News Sentiment. Model 2 has 738 observations and utilizes the constructed news-based investor sentiment indicator using *FinBERT*. As mentioned, the compounded sentiment for every trading day was accumulated from news article texts regarding Corporate Green Bonds published on the day and analyzed using the NLP library FinBERT in Python. The results of the regressions coincide with the ones in Model 1, apart from the change in IV. The regression results show a positive coefficient between FinBERT sentiment and the S&P 500 Green Bond returns across all model specifications. A positive relationship is also what we expected to find (Baker & Wurgler, 2007; Brown & Cliff, 2005; Da et al., 2014; Gao et al., 2022). These results and this trend are insignificant however, with no coefficient even at a 10% significance level. This is contrary to what most literature reports (Piñeiro-Chousa et al., 2021; Reboredo & Ugolini, 2020). Similarly to Model 1, the control variables for Volatility as well as Geopolitical Risk are insignificant.

[21] Significance levels for 2017 at 1%, and 2022, 2023 & 2024 at 5%, all coefficients around 0.25

Model 2: *FinBERT Sentiment Regressions*

VARIABLES	(a) SP500_GreenBond	(b) SP500_GreenBond	(c) SP500_GreenBond	(d) SP500_GreenBond	(e) SP500_GreenBond
FinBERTsent	9.29e-05	2.44e-05	1.90e-05	2.03e-05	1.91e-05
	(0.000103)	(7.96e-05)	(7.86e-05)	(7.83e-05)	(7.79e-05)
SP500_Bond		0.662***	0.617***	0.601***	0.601***
		(0.0796)	(0.0785)	(0.0807)	(0.0807)
SP500_Index			0.0438***	0.0720***	0.0725***
			(0.0164)	(0.0240)	(0.0242)
Volatility				0.00483	0.00494
				(0.00332)	(0.00334)
GPR_Change					-0.000309
					(0.000327)
2015.year	-0.0231	0.0592	0.0695	0.0783	0.0745
	(0.152)	(0.140)	(0.142)	(0.144)	(0.144)
2016.year	0.106	0.136	0.143	0.149	0.151
	(0.162)	(0.128)	(0.130)	(0.130)	(0.129)
2017.year	0.248**	0.272***	0.273***	0.278***	0.280***
	(0.126)	(0.0987)	(0.100)	(0.102)	(0.102)
2018.year	0.0590	0.165*	0.171*	0.173*	0.177*
	(0.116)	(0.0984)	(0.0991)	(0.101)	(0.101)
2019.year	0.198*	0.144	0.152*	0.161*	0.162*
	(0.114)	(0.0889)	(0.0910)	(0.0930)	(0.0931)
2020.year	0.275	0.260**	0.266**	0.266**	0.264**
	(0.212)	(0.115)	(0.116)	(0.118)	(0.118)
2021.year	0.0571	0.142	0.142	0.145	0.146
	(0.110)	(0.0903)	(0.0919)	(0.0940)	(0.0941)
2022.year	-0.107	0.0647	0.0800	0.0923	0.0934
	(0.137)	(0.104)	(0.105)	(0.106)	(0.106)
2023.year	0.157	0.220**	0.219**	0.223**	0.225**
	(0.135)	(0.103)	(0.104)	(0.106)	(0.106)
2024.year	0.248*	0.253**	0.258**	0.260**	0.260**
	(0.146)	(0.104)	(0.106)	(0.108)	(0.107)
Constant	-0.106	-0.186**	-0.195**	-0.203**	-0.200**
	(0.103)	(0.0839)	(0.0861)	(0.0879)	(0.0880)
Observations	738	738	738	738	738
R-squared	0.025	0.558	0.566	0.569	0.569
TIME FE	YES	YES	YES	YES	YES
Mean VIF	2.64	2.50	2.43	2.58	2.48

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficients for both the S&P 500 controls are very positive and significant at the 1% level, which is in line with what we expect due to the nature of their construction being like that of the DV (Zerbib, 2019). The R^2 is also very small in specification 2.a at 2.5%, which infers low explanatory power from FinBERT sentiment on Green Bond returns. The R^2 spikes in the latter specifications, reaching 56.9% in both 2.d and 2.e. The mean VIF fluctuates around 2.5, which would indicate low to moderate multicollinearity between the IV's.

This model also controls for time fixed effects using a year dummy, which is significant in specifications b – e for years 2017, 2020, 2023 and 2024. The positive coefficients indicate that for these years, the average Green Bond returns were higher than the reference group (2014), ceteris paribus. These results are also the same as what occurred in Model 1.

5.2.3 Daily News Sentiment Index Model 3 was included to showcase that investor sentiment constructed from news articles can in fact predict green bond return fluctuations at a significant level. The role was to have a baseline to compare and assess the effectiveness of the constructed sentiment index (FinBERT) from Model 2. The regression results from Model 3 stem from 707 observations and 5 permutations of the established basic model from equation 1. Contrary to the results of Model 2 using FinBERT news sentiment, the Daily news sentiment (NewsSent) reports consistently negative coefficients across all model specifications a – e.[22] The results, however, are also mostly insignificant even at the 10% level, and the coefficients are consistently close to 0 so the implications are limited.

[22] similarly to model 1

Model 3: *Daily News Sentiment Regressions*

VARIABLES	(a) SP500_GreenBond	(b) SP500_GreenBond	(c) SP500_GreenBond	(d) SP500_GreenBond	(e) SP500_GreenBond
NewsSent	-0.000847*	-0.000445	-0.000491	-0.000471	-0.000467
	(0.000495)	(0.000335)	(0.000341)	(0.000333)	(0.000334)
SP500_Bond		0.663***	0.607***	0.584***	0.583***
		(0.0800)	(0.0791)	(0.0805)	(0.0805)
SP500_Index			0.0529***	0.0920***	0.0932***
			(0.0162)	(0.0222)	(0.0222)
Volatility				0.00660**	0.00677**
				(0.00323)	(0.00326)
GPR_Change					-0.000393
					(0.000338)
2015.year	0.0393	0.130	0.144	0.154	0.149
	(0.153)	(0.142)	(0.145)	(0.146)	(0.146)
2016.year	0.0515	0.0846	0.0880	0.0967	0.0986
	(0.165)	(0.122)	(0.127)	(0.127)	(0.127)
2017.year	0.259**	0.300***	0.297***	0.303***	0.305***
	(0.127)	(0.0970)	(0.101)	(0.104)	(0.104)
2018.year	0.0846	0.196*	0.198*	0.198*	0.204*
	(0.119)	(0.100)	(0.102)	(0.105)	(0.105)
2019.year	0.165	0.152*	0.152*	0.159*	0.160*
	(0.112)	(0.0862)	(0.0899)	(0.0930)	(0.0934)
2020.year	0.280	0.285**	0.287**	0.287**	0.284**
	(0.216)	(0.116)	(0.119)	(0.121)	(0.121)
2021.year	0.0752	0.171*	0.167*	0.171*	0.171*
	(0.112)	(0.0893)	(0.0929)	(0.0962)	(0.0966)
2022.year	-0.0600	0.117	0.127	0.141	0.142
	(0.140)	(0.103)	(0.106)	(0.108)	(0.108)
2023.year	0.178	0.247**	0.240**	0.244**	0.246**
	(0.137)	(0.101)	(0.104)	(0.108)	(0.108)
2024.year	0.261*	0.281***	0.284***	0.286***	0.285***
	(0.146)	(0.103)	(0.107)	(0.109)	(0.109)
Constant	-0.117	-0.213***	-0.220**	-0.231**	-0.227**
	(0.105)	(0.0824)	(0.0867)	(0.0898)	(0.0904)
Observations	707	707	707	707	707
R-squared	0.024	0.570	0.582	0.586	0.587
TIME FE	YES	YES	YES	YES	YES
Mean VIF	2.67	2.53	2.47	2.62	2.51

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The model does indicate one significant relationship in specification 3.a however, where albeit negative, the coefficient on NewsSent is significant at the 10% level. Even though 10% is the bare minimum for any interpretations, it's clear that the effect is minimal. With a 1% increase in NewsSent in a day, the daily returns on Green Bonds decrease by 0.000847%. This means that even a large percentual increase in NewsSent will likely have limited impact on Green Bond Returns, ceteris paribus.[23]

Similarly to models 1 and 2, both S&P 500 controls are positive and significant at the 1% level across all specifications. Unlike the previous 2 models, here there is clearly a positive and significant (at 5%) relationship between Volatility and Green Bond returns. The Geopolitical Risk Index remains insignificant in this model as well, with a coefficient slightly negative but close to 0.

The time fixed effects are mostly insignificant in 3.a (except for 2017), however specifications b – e yield significant time trends in years 2017, 2020, 2023 and 2024. 2017 was significant at 1%, while the rest of the mentioned years came out at 5%. This would indicate that like in all models, also here the average returns on Green Bonds were higher in these years compared to 2014, ceteris paribus.

Model 3.a showcases the simple relationship between NewsSent and Green Bond returns, however the model R^2 is still very small at only 2.4%. This is also indicative of the 10% significance of the coefficient. The value of R^2 jumps to almost 60% in specifications b – e, but with a mean VIF of

[23] 1000% increase in NewsSent is only about a 0.847% decrease in Green Bond Returns, ceteris paribus.

around 2.5 for all specifications, we can only infer low or moderate multicollinearity (Dormann et al., 2012; O'brien, 2007).

5.2.4 Hypotheses Evaluation. *Hypothesis 1* tests for the significant relationship between investor sentiment[24] and Green Bond returns. All 3 models developed and evaluated (except for model 3.a) show an insignificant relationship, thus challenging the notion and results of most academic literature which posits a significant positive relationship (Baker & Wurgler, 2007; Brown & Cliff, 2005; Da et al., 2014; Gao et al., 2022). This paper finds no significant relationship between investor sentiment (both market and news based) and Green Bond returns. Furthermore, our models yield both positive (FinBERT) and negative (NewsSent, ISEE) coefficients in the regressions. Therefore, we fail to accept the hypothesis that investor sentiment and green bond returns have a statistically significant relationship.

Hypothesis 2 dives into the long-term viability of using Investor sentiment to proxy Green Bond returns. Based on literature we expected to find that a market-based sentiment indicator (ISEE) will perform better than the news-based sentiment indicator (FinBERT or NewsSent) over a time span of 10 years (Huang et al., 2019). Looking at the R^2 of specification *a*, model 1 using the ISEE as its indicator reports 2.3%, which is the lowest of all models. Models 2 and 3 using the news-based indicators report an R^2 of 2.5% and 2.4% respectively. Considering the full model, specification *e* yields the following R^2 values for models 1, 2 and 3 respectively: 57.3%, 56.9% and 58.7%. This would be indicative that though by a small margin, the news-based models perform better than the market based model in predicting fluctuations in Green Bond returns for

[24] proxied by NewsSent, FinBERT and ISEE

all specifications. This would reject our hypothesis that market-based sentiment indicators perform better, however due to the vastly insignificant results, that conclusion is not crystal clear from the data. Furthermore, these results also challenge the notion of investor sentiment having any sort of predictive ability when used as a proxy for Green Bond returns. Considering other literature however (Baker & Wurgler, 2007; Brown & Cliff, 2005; Da et al., 2014; Gao et al., 2022), the more likely option is an oddly specified model that incorrectly attempts to explain Green Bonds with lacking data or imperfect explanatory variables. More on this in Section 6.

5.3 Robustness Check

In order to support or question the results of the regressions, we need to conduct a robustness check to identify any potential shortcomings of the models. These shortcomings might influence the reliability of the results; therefore it is very important to identify any shortcomings or OLS assumptions that are unsatisfied.

5.3.1 Autocorrelation. To test for model autocorrelation, we opt for the Durbin-Watson test for first-order autocorrelation in the residuals. In OLS time series regressions, a problem occurs when successive data observations are serially correlated, which goes against the OLS assumption of independent error terms (Durbin & Watson, 1950). Table 3 showcases the results of the Durbin Watson Test for each of the 3 models, and the STATA outputs can be viewed in appendix II.

	Model 1: *ISEE*	**Model 2:** *FinBERT*	**Model 3:** *NewsSent*
Nr. Gaps in sample	745	737	706
Durbin – Watson d-statistic	0.0000	0.0000	0.0000

(Table 3: *Durbin – Watson Test for Autocorrelation*)

The Durbin – Watson d – statistic showcases the level of autocorrelation in the regression's error term. A value of 2 showcases no autocorrelation, and values 4 or 0 indicate strong negative or positive autocorrelation respectively (Durbin & Watson, 1950). From Table 3 it's clear, with all 3 models yielding a d-statistic of 0, that there is in fact strong positive autocorrelation in the error term present in every model tested. This means that our model is a biased estimator[25] and the standard errors produced are inaccurate. Furthermore, the R^2 for every model has likely been inflated due to the presence of positive autocorrelation, also explaining the spikes in R^2 when adding more variables to each of the models.

5.3.2 Heteroskedasticity. This paper uses White's test for Heteroskedasticity developed by Halbert White (1980). It is used to determine if the variation of the error term is constant over observations. For every model, the results of the test are presented in Table 4. Two other measures are given by this test, namely Skewness and Kurtosis. Skewness is a measure which indicates whether the data Is skewed to either the right (positive) or left (negative) tail. Kurtosis is the measure which indicates how well the data follows the normal distribution. The null hypotheses for the Heteroskedasticity, Skewness and Kurtosis tests are: Homoskedasticity, symmetrical distribution and Mesokurtic distribution respectively. In terms of Heteroskedasticity, all models

[25] challenging the notion that we can accurately answer the hypotheses

yield a significant p-value at 1%, rejecting the null hypothesis of homoskedasticity, indicating heteroskedastic standard errors. In order to counteract this, we run the STATA regressions using the *,robust* command for robust standard errors.

	Model 1: *ISSE*		**Model 2:** *FinBERT*		**Model 3:** *NewsSent*	
Source	Chi^2	p-value	Chi^2	p-value	Chi^2	p-value
Heteroskedasticity	445.14	0.0000	434.06	0.0000	430.95	0.0000
Skewness	144.49	0.0000	141.26	0.0000	142.25	0.0000
Kurtosis	3.29	0.0696	3.45	0.0632	2.94	0.0864

(Table 4: *Heteroskedasticity, Skewness and Kurtosis in all models*)

All models also report a significant p-value (at 1%) for skewness, and with a large positive Chi^2, this could only mean that the distribution is heavily positively skewed (Williams, 2020). Kurtosis is the only test condition that does not yield any significant results, thus here we fail to reject the null hypothesis and accept that we have a mesokurtic distribution with moderate tails and peak (Williams, 2020).

5.3.3 Stationarity. To test for the presence of a stationary series, or a series whose statistical properties do not change over time, the augmented Dickey-Fuller test was used. The full output for our model can be found in Appendix IV. The Test Statistic is much larger than the 5% or 1% critical values while having a p-value of 0.000. Thus, the null hypothesis of stationarity is rejected, and this series seems to have a unit root (Enders & Lee, 2012). This will yield lower accuracy of results and can tamper with the magnitude and direction of the relationships regressed in OLS. A unit root indicates that the statistical properties (mean, variance…etc.) are not constant over time. This can lead to a spurious regression which can also explain the high R^2 values in the models (Enders & Lee, 2012).

5.3.4 Multicollinearity. Even though all 3 models yielded acceptable VIF results[26], further analysis was conducted, nonetheless. Figure 1 showcases a correlation matrix between all the variables in the models, to pinpoint the cause of the drastic increases in R^2. We can see that the significant correlations are between the various S&P 500 Index derivatives[27], the CBOE volatility index and Green Bond returns. The correlations are significant at 1%, and some are very high at above 50% correlation which indicates multicollinearity in the regressions (Dormann et al., 2012; O'brien, 2007). It is good however to see the low correlations between the various IV's introduced in the models. Furthermore, Geopolitical risk is uncorrelated and insignificant (here and in all models), thus we can assume that it does not influence our model. These results highlight that the control variables used are highly collinear, thus decreasing the overall accuracy of the model and interpretability of the coefficients (O'brien, 2007).

Figure 1 ; Correlation Matrix : *Variables*

	(1)							
	SP5~x	SP5..	S~G~d	Vol~y	GPR~e	Fin~t	New~t	ISE~e
SP500_In~x	1.00							
SP500_Bond	0.51***	1.00						
SP500_Gr~d	0.47***	0.75***	1.00					
Volatility	-0.74***	-0.20***	-0.18***	1.00				
GPR_Change	0.01	-0.01	-0.03	0.03	1.00			
FinBERTs~t	0.04	0.03	0.03	-0.04	-0.02	1.00		
NewsSent	0.01	-0.04	-0.06	-0.03	0.02	0.01	1.00	
ISEE_Cha~e	0.04	-0.06	-0.04	-0.06	-0.00	0.01	-0.00	1.00

[26] see Models 1-3 in section 5.2
[27] S&P 500 Index and S&P 500 Bond Index

5.3.5 Normality of Residuals. To check the normality of the error term, residuals were computed in STATA under each model[28]. The Shapiro-Wilk test was performed to check whether they are normally distributed. The resulting p-values for every model are displayed in Table 6.

	Shapiro- Wilk p-value		
	Model 1: *ISSE*	Model 2: *FinBERT*	Model 3: *NewsSent*
Residuals	0.0000	0.0000	0.0000

(Table 6: *Shapiro – Wilk Normality test*)

It is clear from the table that all models are significant at 1%, and we reject the null hypothesis of normal distribution. This indicates that our data distribution might not be well suited for OLS regression, thus influencing the regression results and the applicability of the conclusions drawn[29] (Mohd & Wah, 2011).

6. Discussion

The primary findings of this paper challenge the established notion that sentiment significantly influences financial markets including green bonds (Baker & Wurgler, 2006; Da et al., 2014; Gao et al., 2022; Piñeiro-Chousa et al., 2021). Despite extensive analysis, the results did not indicate a statistically significant relationship between the sentiment indicators studied and the Green Bond index returns. This kind of result inherently raises a question as to why this is the case, and what are the implications for further research.

[28] This test is done prior to the log-returns transformation

[29] The full output for the test and each model can be found in Appendix III

6.1 Contrasting Sentiment Effects

According to the mainstream literature on investor sentiment (Baker & Wurgler, 2006; Brown & Cliff, 2005), there is a significant positive relationship between sentiment and the returns on stocks and bonds. Our results, however, showcase a different story. Not only do we not yield a single significant sentiment indicator in our regressions, Models 1 & 3 also show negative coefficients. This result is the opposite of what research predicts, and there are some reasons why this may be the case. One of the reasons can be that the Green Bond market does not operate with the same dynamics as a traditional stock or bond market would (Friede et al., 2015; Reboredo, 2018). One clear indication of this is the largely environmental focus of Green Bond investors (Piñeiro-Chousa et al., 2021). This also opens an avenue for further analysis, to see whether green bonds behave differently based on sentiment driven market fluctuations.

6.2 Validity of Approach

Another large reason for the contradictory results is the approach taken to answer the developed hypotheses. First and foremost this paper set out to study a timespan of 10 years, however with less than 800 observations, not even 30% of all trading days in those 10 years are covered. When trying to establish whether sentiment influences the returns on a daily basis, coverage of most if not all days is important. Due to the lack of news articles used, and consequently sentiment for many days, the rest of the variables were also similarly contracted because of it. It is not unwise then to believe that the effects of investor sentiment on any given day were likely lost due to the absence of data for the following day/s.

The python library used to generate compound daily sentiment scores (FinBERT) is free to use and can be applied to a plethora of different texts for which sentiment analysis can be useful. In simple terms, this library is not specifically trained or built for news article analysis, therefore there may be more advanced or appropriate methods to use instead (Devlin et al., 2019; Yang et al., 2020). Machine learning algorithms or simply curated code that is tailored for news article sentiment would be the most appropriate choice.

Furthermore, only the highly correlated S&P derived control variables were significant, indicating a possibly badly designed model where the indicators were not well matched to the specific nature of the Green Bond market (Friede et al., 2015). This is clearly seen from the drastic and consistent jumps in R^2. Geopolitical risk seems to yield no impact on our model as well, which would indicate that investments in green bonds are likely immune to sudden rises in international tensions. This is probably because the goals of green bonds (ESG related) supersede the most immediate market shock mechanisms (Reboredo, 2018). This is supported by the fact that also Volatility is insignificant in Models 1 & 2. Model 3 however displays significant positive coefficients on volatility, indicating that an increase in market volatility does in fact increase the returns on green bonds, however marginally. This significant result, being contrary to the Volatility results in the other models, raises some questions. It is plausible, that in Model 3, NewsSent has decreased collinearity with Volatility, therefore leading to increased statistical significance. Even though the VIFs do not entirely support this notion. Alternatively, NewsSent might implicitly account for certain factors that the other models do not. If these factors are omitted, and they happen to correlate with VIX, it could cause deflated significance levels in Models 1 & 2. These could potentially explain why seemingly similar models yield opposing results.

Lastly we see a common time trend in the regressions, where apart from specification *a* for each model, there were significant positive coefficients on various years in the other specifications. Most significance was seen during the years 2017, 2020, 2023 and 2024. This indicates that the average returns on the S&P 500 Green Bond Index were higher during those years compared to 2014 returns, ceteris paribus. There is no clear indication why these years would stand out among the rest, but here is the best estimate of why it may be so.

In 2017, just shortly after the Paris Climate Agreement, there was an upswing in global economic growth, which could have stimulated financial markets. According to the World Bank (2017), the United States along with other developed nations were expected to gain momentum in 2017. This was in part due to improving global financing conditions at the time. Low market volatility despite elevated policy uncertainty could have also further contributed to this effect. On the other hand, the global narrowing of corporate bond spreads (World Bank, 2017) would counteract this claim, but we can posit that the Green Bond market might act separately from the bond market as a whole (Reboredo, 2018).

In 2020, amidst the COVID-19 pandemic, many economies including the U.S documented economic contraction rather than expansion (Nam, 2020). This was mainly due to the chaos surrounding pandemic regulations and overall increase in market volatility and uncertainty. Keeping this in mind, the indicated higher returns on green bonds support the notion that the green bond market does not comply the same way to outside stimuli as a conventional bond or stock market might (Reboredo, 2018). In this way, green bonds can provide a safe haven for investors through otherwise tumultuous times. Further research into this concept would need to be undertaken to identify the cause more accurately.

In 2023, and until April 2024 there are also significant trends between the regression models. This is the period which indicates the end of the COVID-19 pandemic, and the recovery of global trade. According to Bloomberg (2024), one major step forward was the increase in corporate and sovereign green bond issuance, which totaled $575 billion in 2023. These higher returns are despite an increase in inflation and worsened market conditions, which strongly suggests global commitment to the climate goals set by international agreements. This also supports the notion of green bonds being a means to a sustainable end.

Continuing from the discussion of the results, the robustness checks indicated more about the appropriateness of the chosen approach.[30] The Durbin – Watson autocorrelation test yielded indications of autocorrelation in the error term in each of our models (Durbin & Watson, 1950). White's test for Heteroskedasticity pointed towards high levels of both heteroskedasticity in the error term as well as a positively skewed distribution (Williams, 2020). To account for this, the regressions are run using robust standard errors. No evidence was found however, to support any presence of Kurtosis. Furthermore, the Dickey – Fuller test for Unit root also indicated that all models might be running spurious regressions, which indicates that our series are non-stationary (Enders & Lee, 2012). The models also showcased relatively healthy values of VIF[31], however further analysis of the correlation matrix showcases high levels of correlations between explanatory variables which inflates the R^2 in our models (Dormann et al., 2012; O'brien, 2007).

[30] See section 5.3
[31] VIF consistently around 2.5 for all models and specifications

Lastly, the Shapiro-Wilk test for the normality of residuals further indicates that our dataset is abnormally distributed, which influences our resulting OLS regressions (Mohd & Wah, 2011). To correct for the normality of residuals, the regressions are run in log-returns.

Most of the robustness tests indicate that the models presented do not satisfy the OLS assumptions for an unbiased estimator. It is likely that I have built biased models that do not reflect the relationships occurring in the financial markets entirely. Therefore, further analysis of these relationships is necessary to confirm to what extent the results presented here deviate from the truth.

7. Conclusion

In conclusion, this paper sought out to contribute to the already growing literature on corporate green bonds. The aim was to evaluate the effectiveness of various sentiment indicators in explaining the fluctuations in corporate green bond returns. Differentiation between market-based and news-based sentiment data would aid in gauging their relative accuracy in predicting the S&P 500 Green Bond Index. Our findings yield several implications and practical considerations for future research.

In summary, the results did not support the notion of either one of the hypotheses including the positive relationship between Green Bond returns and investor sentiment as presented in literature (Baker & Wurgler, 2007; Brown & Cliff, 2005; Da et al., 2014; Gao et al., 2022). No significant relationship between Green Bond index returns and any of the independent variables was established (see section 5.2). All models, (ISEE, FinBERT and NewsSent) failed to provide any substantial predictive power in the fluctuations of Green Bond returns.

The main reason quoted to be the cause of the seemingly opposite relationship is data quality. Though daily frequency is used, FinBERT sentiment data is not complete for all the days in the time range, thus the daily influence of news on the market can be skewed with missing days (Ahn et al., 2022). Furthermore, the Robustness checks conducted in section 5.3 point to several problems with the data and regressions. First, we find strong positive autocorrelation of the error term in every model, this goes against OLS assumption[32] making the estimated results biased (Durbin & Watson, 1950). Furthermore, using the White's test for Heteroskedasticity, we find strong evidence of heteroskedastic standard errors, as well as the data being heavily positively skewed (Williams, 2020). This is amended in STATA via robust standard errors. Furthermore, using the Dickey Fuller unit root test, we found that all models are likely non-stationary, leading to spurious regressions and an inflated R^2 (Enders & Lee, 2012). Tests for Multicollinearity also indicate a significant correlation between the control variables, which can lead to an inflated model fit (Dormann et al., 2012; O'brien, 2007). Lastly, using a Shapiro-Wilk test, the data distribution seems to not follow the normal distribution, thus making it unfit to an extent for use in OLS regressions (Mohd & Wah, 2011). The log returns were taken then to counteract for this issue.

Despite this paper not finding any significant relationship between Investor sentiment and Green bond returns, it still sheds light on the issues and pitfalls of traditional sentiment analysis. For further development or research, we recommend using more robust sentiment data that covers at least most of the days in the time period investigated. Furthermore, the choice of sentiment indicators matters a lot, as is clear by the vastly insignificant results presented. It is possible that common sentiment indicators are not all well suited to capture the intricate and new field of green finance and corporate green bonds within it (Friede et al., 2015). An alternative approach to

[32] Assumption of no Autocorrelation in the Error Term

constructing investor sentiment would be advisable, the suggestion made here is using indicators that are tailored to ESG factors or to other measures of corporate sustainability performance. These could fare better than the market/ news-based indicators presented here. Furthermore, the FinBERT sentiment calculated in this paper was based on a albeit financial, but readily available python library. Machine learning methods can be implemented instead to garner a more realistic sentiment score per day (Devlin et al., 2019; Yang et al., 2020). Other approaches can also be implemented to regress using panel data instead of time-series to yield a more accurate regression between firms.

Even though the results were limited, with any luck, this study can still promote the importance of continuously researching the ever-evolving green finance market. Important temporal trends were established, and various explanatory variables evaluated for the purpose of this paper. The data presented contributes to the growing body of literature on Green Bonds and the analysis of Investor Sentiment, providing foundational work for future studies to build on.

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9. Appendix

I Sentiment Articles

Year	Number of Articles
2014	42
2015	63
2016	57
2017	76
2018	86
2019	90
2020	82
2021	145
2022	156
2023	138
2024	50
Total	**1647**

II Autocorrelation Test results

Model 1 (ISEE):

```
. estat dwatson

Number of gaps in sample:  745

Durbin-Watson d-statistic( 16,   746) =         0
```

Model 2 (FinBERT):

```
. estat dwatson

Number of gaps in sample:  737

Durbin-Watson d-statistic( 16,   738) =         0
```

Model 3 (NewsSent):

```
. estat dwatson

Number of gaps in sample:  706

Durbin-Watson d-statistic( 16,   707) =         0
```

III Shapiro Wilk Test

Model 1 (ISEE):

```
. swilk residuals
```

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
residuals	746	0.93149	33.100	8.561	0.00000

Model 2 (FinBERT):

```
. swilk residuals
```

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
residuals	738	0.93261	32.239	8.493	0.00000

Model 3 (NewsSent):

```
. swilk residuals
```

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
residuals	707	0.93687	29.048	8.223	0.00000

IV Dickey Fuller Unit Root

Dickey-Fuller test for unit root Number of obs = 743

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-29.935	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000