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A Correlation Study on the Relationship between Credit Default Swap (CDS) Spreads and ESG Sentiment in the Banking Sector

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Abstract

This study examines the influence of online ESG sentiment on credit market price movement in the banking sector. By employing a panel regression model with fixed effect for firms and time, the study's findings indicate an inverse relationship between online ESG sentiment and CDS spread in accordance, to some extent, with previous literature. Additionally, the study investigates the impact throughout different time periods, regional effect and sentiment asymmetry. However, limited supporting evidence is found for online ESG sentiment and CDS spread in the banking sector when it comes to regional differences, asymmetric relationships for the ESG sentiment and during periods of economic uncertainty. The study contributes insight into ongoing research on understanding ESG's impact on credit risk in the banking sector and indicates that incorporating ESG could help banks in managing their risk mitigation

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1. Introduction

The influence of media on firms' financials has been a recurring subject in academia and numerous empirical studies have found evidence of news sentiment influencing price movements on the credit market (Smales 2016; Yang et al., 2020; González-Fernández & González-Velasco 2020). As news spread faster than ever today, research on credit and default risk incorporates alternative data sources to a larger extent e.g. such as News Sentiment (Smales 2016; Yang et al., 2020) and Google Searches, (González-Fernández & González-Velasco 2020). These studies have revealed correlations between changes in credit risk, such as CDS spreads, and various metrics of sentiment.

Environmental, social and governance factors, most commonly known by its abbreviation ESG, in the financial sector (Galetta et al., 2023) has evolved from being mere buzzwords into finding their way into an increasing number of regulatory frameworks being implemented (e.g. Corporate Sustainability Reporting Directive, EU Taxonomy & SFDR). Moreover, sustainable assets have grown globally from $5 billion in 2018 to $2.5 trillion by 2022 (McKinsey's, 2022). The rising interest in ESG has, as of 2022, caused approximately 79% of leading companies to disclose Corporate Social Responsibility information according to KPMG's *Survey of Sustainability Reporting* (2022). The rating agency S&P reports that over 1,000 of their credit rating decisions between 2015 and 2017 took ESG factors into account. Given the escalating popularity of ESG it is crucial to explore to what extent the fixed-income markets incorporate ESG information. This has obviously been an interest of investment managers and rating agencies for some time, who have posted articles discussing the topic e.g. on pricing ESG in the credit market and predicting CDS spreads using ESG ratings (Federated Hermes, 2017; S&P Global Market Intelligence, 2022). Academics have also responded with numerous studies conducted on examining the correlation between ESG factors and various credit metrics, such as CDS contracts, and empirical evidence suggest ESG factors can help to explain a firm's probability of default (Zhang & Zhao, 2022; Barth et al 2022; Bonacorsi et al., 2022).

The overall focus on these studies have mostly been on firms in general (Galetta et al 2023). However, banks are particularly interesting according to Galetta et al. (2023) as the Basel Committee on Banking Supervision (BCBS, 2022) has highlighted practices for banks to consider major ESG risks in their risk management systems and climate-related drivers on the credit market. Galetta et al (2023) also notes how BCBS principles (2022) implies how banks should be aware of reputation and regulatory compliance risk associated with climate-sensitive investments and organizations. Sustainability is not just an ethical question for banks, but may soon enough also become an economic and existential question (KPMG, 2021). Banks play a crucial role by channeling financial flows toward sustainable activities, supporting industries and governments in achieving their ESG targets determines which companies receive financial support, enabling them to play a vital role in promoting corporate social responsibility (KPMG, 2021; Galetta et al., 2023). Therefore, banks are in reality required to follow ESG practices, and may reap rewards from it, however, they find themselves under constant scrutiny for their ESG risk exposure.

Previous research on ESG-related risks conducted on banks in particular (Di Tomasso & Thornton 2020; Galetta et al 2022; Agnesa et al 2023) have used conventional ESG ratings rather than alternative data, and the ones who have done so, however, have in general not focused on banks in particular. In our contribution to bridging this gap, we investigate whether corporate credit spreads exhibit reactions to ESG-related news. More specifically, we use a firm-specific ESG sentiment score for banks and study the relationship on the CDS market to discuss a couple of hypotheses based on previous research. Our aim is to contribute to studies on credit risk mitigation for banks related to sentiment by conducting a linear regression model on a sample of some of the biggest banks globally and study their relationship on average between credit risk measurements and sentiment online related to ESG. Our research found significant evidence of an inverse relationship between ESG sentiment and CDS spread among banks.

2. Conceptual Framework

Credit default swaps (CDS) allows market participants to trade credit risks. The product is a contractual agreement directed towards investors of bonds to insure themselves against the risk that their company bond defaults (Hull, 2006). A bond investor can buy a CDS contract which transfers the bonds' credit risk for a company, known as the *reference entity,* to the seller of a CDS contract, which the seller accepts in exchange for periodic payments over a specified time period. If the company would not be able to meet its financial obligations, meaning a default occurs, the buyer of the CDS contract has the right to sell the bonds for its face value and the seller of the CDS contract has to buy the bond for its face value, known as its notional principal. (Hull, 2006).

CDS are widely recognized as the predominant form of credit derivatives (Bomfim, 2022) and are usually traded with $10 million or more in notional value, making buyers of the CDS market exclusively to be institutional investors. The CDS spread refers to the price of the CDS that represents the cost of insuring the default of a borrower and it is typically expressed as a basis points (bps) (Angelini, 2012). A crucial parameter in CDS pricing is the amount of credit risk associated with the underlying reference entity (Byström, 2005). The credit risk can be derived from credit rating agencies that specialize in assessing the risk associated with individual firms in meeting their financial obligations. A second approach is to use traditional scoring models using accounting data. A final approach is to base the credit risk assessment on the firm's market prices of a firm's asset to measure its credit risk (Byström, 2005), which is the basis of the Merton Model (1974).

The Merton Model (1974) utilizes a structural approach to evaluate the risk of a credit event, such as a default, for a firm. Merton's framework (1974) assesses the credit and default risk of a public company as an alternative to credit ratings or accounting models. It extends the Black and Scholes pricing model (1973) by considering a firm's equity as a European call option on its assets with a strike price equal to the face value of debt. The main idea is to demonstrate how the probability of a company's default can be calculated based on the market valuation of companies, making certain assumptions about the evolution of assets and liabilities. The variables utilized in Merton's model (1974) are the volatility of the firm's stock, equity, assets, debts, and the risk-free interest rate. When the value of the asset falls below the value of the debt, the firm is considered to be in default. An essential assumption is that the default event can only occur when the debt matures and repayment is due. By deriving asset values and volatilities from quoted stock prices and balance sheet information, the Merton (1974) model provides instant updates of a firm's default probability. The model can be used to estimate either the risk-neutral probability of default for the company or the credit spread on the debt (Byström, 2005). Fluctuations in credit default swap (CDS) spreads, as predicted by the Merton model, are mainly driven by leverage, asset volatility, interest rates and the risk aversion of investors (Tang & Yan, 2012). As a result, when investors become more risk-averse, there is a tendency for spreads to increase. Tang and Yan (2012) suggests that these variables play a significant role in shaping the changes observed in CDS spreads within the Merton model framework.

Previous research notes the rather uncertain effect ESG practices might have on a company’s credit risk (Barth et al, 2022). From one standpoint, a high ESG score might imply a well-run company, resulting in more stable cash flows in comparison to one with a lower score, which according to the Merton model (1974) implies a financially healthy company that is less likely to default. Alternatively, a high ESG score might also indicate that firms spend too much of their resources on ESG activities resulting in a less well-run firm, hence higher risk (Goss and Roberts, 2011).

3. Literature review and hypothesis development

The relationship between sentiment on firm-specific news and credit risk has been studied in prior research for firms in general (Yang et al, 2020; Naumer & Yurtoglu, 2022) as well as for banks (Smales, 2016; González-Fernández & González-Velasco, 2020). However, the term sentiment lacks a universally accepted definition in literature due to its association with a range of attributes (Pandey & Sehgal, 2019) and, therefore, a variation of metrics for sentiment have been used in the previous literature. To exemplify, prior research have examined the relationship between sentiment expressed in newswire messages and changes in credit measures and found a notable and negative correlation between the two variables, providing evidence to the notion that positive news reduces credit risk while negative news increases, both for firms in general (Yang et al, 2020; Naumer & Yurtoglu, 2022) and banks in particular (Smales 2016).

Regarding the findings on companies in general, sentiment based on firm-specific news and credit spread was conducted by Yang et al. (2020). Their results demonstrated a negative correlation between news sentiment and CDS spreads and the impact was larger for firms of smaller size, with lower ESG ratings and higher fluctuation in their earnings forecast. Yang et al. (2020) also found that the evidence for the relationship between firm-specific news sentiment and CDS spreads was particularly robust during the 2008 financial crisis and for news characterized by negative sentiment. Additionally, news articles that are more closely tied to firms' exhibited a stronger correlation with CDS spreads (Yang et al, 2020).

In Smales (2016) study, of similar character, investigated firms in the banking sector. Smales (2016) results also witnessed a significant and negative correlation between news sentiment and changes in CDS spreads for banks in their results, aligning with the expectation that positive news reduces credit risk while negative news increases it. In addition, the results also indicated that the sentiment of news stories, rather than the mere presence of relevant news, held importance and that the relationship between the banks CDS spread and their news sentiment was asymmetrical. More specifically, negative news induced a stronger effect on the CDS spread than positive news. Worth mentioning is that Smales' (2016) findings were evident through larger coefficient estimates for news sentiment and the statistical significance of the volume of news articles during the crisis interval of 2007-2009. Another type of sentiment where evidence indicates a correlation between CDS spread and Google searches (González-Fernández

& González-Velasco 2020). Google searches better reflect investor sentiment according to González-Fernández & González-Velasco (2020) and their findings suggest a strong correlation between the Google sentiment and bank CDS. González-Fernández (2020) therefore argues that banks and financial authorities can utilize Google data to develop their credit risk models.

Changes in news sentiment and credit risk for firms in general have been studied where ESG factors also have been incorporated (Naumer & Yurtoglu, 2022). Naumer and Yurtoglu (2022) findings did not support any significant relationship between news sentiment in general and CDS spread, however, they found that whether the news was related to ESG or non-ESG, from financial as well as from mass media, influenced CDS spreads. Also worth noting that Naumer and Yurtoglu (2022) emphasize that not only does the content (ESG or non-ESG) matter but also the tonality of the news. Although the majority of previous studies on the relationship between ESG and financial performance have in general focused on the equity markets there has been made more research on the credit markets' connection to ESG-related risk factors (Naumer and Yurtoglu, 2022; Johanson et al. 2020; Jang et al., 2020; Zhang et al., 2022).

To emphasize on the potential role of ESG sentiment, A study on Chinese listed firms from 2022 shows that firms with higher conventional ESG ratings exhibit lower probability to default and higher conventional ESG ratings mitigate the default risk, which increases with the term structure of default risk. This finding implies that ESG factors are decently priced in the Chinese credit market and ESG performance plays a significant role in credit risk management. Papers also encourage policyankers to consider implementing ESG in their portfolio construction thus it potentially decreases the default risk (Zhang et al. (2022). Similar evidence was found in Europe and US in a study by Barth et al (2022) whose results indicate higher environmental performance being linked to lower CDS spreads. Moreover, the risk mitigation effect of ESG is stronger in Europe compared to the US and it varies across different quantiles (Barth et al, 2022). Overall, the results suggest that incorporating ESG risks into credit risk models can improve credit analysis and risk management for investors, and ESG ratings can enhance performance measurement and predictions of credit rating changes. A study done by Galletta et al. (2023) on the relationship between ESG scores and operational risk in global banks suggests that higher ESG scores are negatively associated with operational risk. Galetta et al. (2023) also found evidence indicating that previous period ESG related performance can impact banks operational risk, indicating that higher previous ESG score could decrease operational risk in the coming period which allows for banks better credit rating. This study sets itself apart from prior research by examining the ESG profiles of performance and controversies within the framework of reputational risk. The findings reveal a clear inverse correlation between the combined ESG scores of banks and operational risk. Companies involved in ESG scandals suffer severe reputational and, consequently, financial damage and Galetta et al (2023) describe how exposure to ESG risks is associated with greater visibility in the market and thus increases the vulnerability of some banks to the negative effects generated by non-compliance with ESG principles. The study supports supervisory authorities on the importance of ESG drivers on credit risk among others in the risk management framework (Galetta et al, 2023). Based on the prior research we can see some uncertainty from lack of evidence on whether specifically ESG sentiment would have a significant correlation with CDS spread in the banking sector. The majority of recent studies with some indication of an existing relationship are conducted on firms in general. Additionally, the asymmetrical relationship between sentiment and CDS spread described in previous research is also of interest (Smales, 2016; Sabbaghi, 2022). The following two hypotheses were created.

Hypothesis 1: A significant negative relationship between ESG sentiment and credit measures exists such that positive (negative) ESG sentiment results in decreasing (increasing) credit risk.

Hypothesis 2: A relationship between ESG sentiment and credit measures is asymmetric such that negative ESG sentiment induces a more significant response than positive ESG sentiment.

Previous research on the relationship between ESG and CDS spreads have found regional variations (Barth et al. 2022). Also, studies have found evidence of ESG to have risk mitigated effects only in countries with high average ESG ratings (Stellner et al., 2015). It is worth noting that studies tend to compare mostly Europe with the US, for example Dyck et al. (2019) report that European countries occupy the top positions in an environmental and social-based ranking of 41 global countries. the notion that Europe provides a sustainable environment in which stakeholders reward risk-reducing ESG investments more than in the US. El Ghoul et al. (2017) argues that the value of ESG is amplified in an environment where the absence of supportive market institutions increases transaction costs and restricts access to alternative sources of financing. The research reveals that the average efficiency of credit markets in the United States surpasses that of nearly all European countries. This suggests that US companies experience lower transaction costs and enjoy easier access to alternative financing options compared to their European counterparts. As a result, the credit risk reduction effect of ESG in Europe could be attributed to a decrease in transaction costs within the less efficient credit markets of Europe. Another factor influencing regional variations in the cost of equity for high ESG firms could be the level of investor protection in different countries. Thus, in this research we will test for ESG variation depending on regional differences. Previous literature has found the financial value of ESG to vary depending on the geographical region (Attig et al., 2013; El Ghoul et al., 2017) for firms in general. Previous studies have found ESG to have risk mitigated only in countries with high ESG ratings (Stellner et al., 2015). Another possible explanation for regional variations in the effectiveness of ESG risk mitigation could be attributed to disparities in transaction costs. A study by Breuer et al. (2018), suggests that lower costs of equity are observed only for high ESG firms in countries where investor protection is robust. The underlying notion is that inadequate investor protection may allow corporate managers to extract personal benefits through ESG investments. Interestingly, (e.g. *Corporate Sustainability Reporting Directive*, *EU Taxonomy & SFDR)* (Bruno & Lagasio, 2021) and is said to be leading the way globally in incorporating ESG into the business world. Therefore, we have constructed a hypothesis to investigate whether there are regional differences in our sample.

Hypothesis 3: There exists a difference in the significance and the impact of ESG sentiment on credit risk measures between banks in the US and in Europe.

Finally, research of ESG sentiment and CDS spread have found variation in the results under uncertain periods of economic instability, such as the great financial crisis where evidence has been found that news sentiment effect is more robust on CDS spread under crisis (Yang et al. 2020). Also, The relationship between news sentiment and credit risk becomes more pronounced during crisis periods, aligning with a time when the quantity of news articles is at its highest and news availability greatly impacts CDS spreads (Smales, 2016). Because the news sentiment has stronger effect on CDS spread we have firm belief that it applies for ESG sentiment, this is why we want to test for hypothesis below:

Hypothesis 4: The reaction of credit measures to news sentiment varies during different economic circumstances, in our case before and during the Covid-19 pandemic.

4. Methodology

4.1 Sample

Our sample was initially derived from a list of the top 100 banks with the highest total assets under management globally in 2023 (S&P Global, 2023). Thereafter, the banks on the list were restricted based on the availability of data on the ESG sentiment scores, reported CDS spreads and geographical location, which resulted in a total of 19 banks: seven in the US and ten in Europe. The list of the banks used in our study is provided in the appendix (see Appendix A) and the sample remains the same for the first hypothesis.

The first hypothesis investigated the entire sample of banks. For the second hypothesis a new categorization of the original sample into two subgroups was created by separating positive and negative ESG sentiment scores resulting in two subsamples. The third hypothesis used a subsample where banks from the United States (7) and Europe (10) were divided in order to investigate regional variations. For the last hypothesis, we divided our sample into two subgroups, one capturing the timeline up until the Covid-19 was declared a pandemic by WHO (March 2013 to March 2020) and a second period until the end of our sample (March 2023). The ESG Sentiment scores consisting of zeros were removed. This division was made to investigate whether the relationship of ESG sentiment on CDS spreads varied during times of uncertainty.

Our sample consists of monthly observations because of previous research noting that the lack of daily trading of CDS contracts makes a daily frequency ratio less practical for an academic study (Tang & Yan, 2008). Consequently, the data for all the variables consists of monthly observations. The investigated period is a ten year interval to compensate for the fairly few observations due to the restriction to monthly data points, starting from the month we gathered our data ultimately resulting in our period ranging between March 2013 until March 2023. All the data with nominal values were converted to US dollars before regression analysis.

4.2 Dependent variable

The CDS spread serves as a reliable proxy for banks credit- and default risk, as suggested by Agbodji (2022). The bank's CDS spreads were obtained from *S&P Capital IQ*. The selected term to maturity for the CDS contracts in our study is five years, as it is the most commonly traded CDS contract (Smales, 2016). This choice ensures that the price changes are captured with utmost accuracy, and it aligns with the conventions followed in previous academic papers. Moreover, extensive research has shown that CDS spreads exhibit a strong response to both firm-specific and macroeconomic variables, such as liquidity and the COVID-19 pandemic, as highlighted by Apergis et al. (2021).

4.3 Explanatory variables

The ESG sentiment score is obtained from *Sanctify Financial Technologies*, a company that uses artificial intelligence to filter and categorize online public text sources along ESG related topics specifically for listed companies and finally provide a sentiment score of the content in the text files. The public, online sources are e.g. news magazine’s websites as well as business press and the scores are updated on a daily basis. This enables us to analyze the impact of a large volume of public firm-specific information online throughout our period. In our study, we utilize a combined ESG sentiment score, which is calculated as the average of their Environment, Social, and Governance scores. Furthermore, the sentiment score also takes public text sources posted over the last twelve months into account, however, it's important to note that Sanctify does not consider the importance of different news sources or the industry or sector of the company. Ultimately it produces a score within the range of -100 to 100.

4.3.1. Firm-specific control variables

Our first group of control variables are firm-specific and gathered from *Eikon Refinitiv* (Thomson Reuters Eikon). The correlation between asset value and equity value plays a crucial role in determining a company's probability of default, as noted by Merton (1974), and consequently, the CDS (Credit Default Swap) spread. Previous research, such as Drago et al. (2016), and Smales (2016), has often incorporated financial leverage as a factor influencing this relationship. However, the definition of the leverage proxy varies across these studies. While some employ book value, others utilize market value. In our analysis, we adopt the same method for leverage Smales (2016), it is determined by dividing liabilities by the market capitalization of the bank. Lower leverage will decline the CDS spread such that lower leverage means that firms have a lower probability to default.

Multiple studies have consistently indicated an inverse correlation between stock returns and CDS spreads. Notably, a negative relationship between the single-name CDS spread and the equity return of firms has been identified for both US and European CDS markets, as demonstrated by Audzeyeva and Wang (2013). Furthermore, Merton (1974) also discussed a negative association between firm stock returns and the probability of default, promoting the use of stock returns as a firm-specific variable in our model. This relationship implies that higher returns are indicative of lower CDS spreads. That is why the stock return is an essential firm variable to understand the change in CDS spread.

Market cap serves as a significant determinant of CDS spreads, exhibiting a positive relationship with CDS spreads. Market cap is defined as price per share multiplied by outstanding share. It represents the total value of a company's shares of stock and enables investors to assess the perceived value of the company by the public. Market cap is a commonly used term to denote the size of a company, as determined by the aggregate value of its stock, in accordance with AICPA (2013, p201-210). Consistent with this, higher market capitalization is indicative of greater firm creditworthiness, resulting in decreased CDS spreads. This notion aligns with the Galil et al. (2014) study that a higher market capitalization enhances the reliability of the firm. Market capitalization as well as asset management are very important factors for a bank's well being, the higher the market cap and assets to lower the probability of default in other words “Too big to Fail”. That is Market cap is used as a firm-specific variable in this study.

Similar to market capitalization, the total assets under managed by a bank play a crucial role in enhancing its creditworthiness, leading to a reduction in CDS spreads, and the factors have been used in several relevant studies. A firm's assets are a significant determinant of its value and its capacity to meet debt obligations, hence influencing its probability of default (Apergis, 2021). Empirical evidence suggests that a stable increase in total assets and reduced volatility in the underlying assets of a firm contribute to a decrease in its credit spread. Consequently, the total assets of banks are of utmost importance in assessing their creditworthiness and long-term viability (Di Febo et al., 2015).

4.3.2. Macroeconomic control variables

The macroeconomic variables included in our study is based on Smales (2006) study. The first one is the 3-month Treasury bills which are widely recognized as a benchmark for short-term risk-free interest rates and it works to use as a proxy for European banks as well (Smales, 2016). They serve as a low-risk investment instrument issued by the government, functioning as a reference point for assessing the cost of short-term borrowing (Drago, 2016). In our study, we incorporate a risk-free rate of return as a fundamental point of comparison. By comparing the yields of CDS spreads with the risk-free rates offered by Treasury bills, this premium reflects the additional compensation investors demand assuming the heightened risk tied to a bank's creditworthiness.

Furthermore, Smales (2016) demonstrated that CDS spreads respond to term spread. The term spread is defined as the difference between 10-year and 3-month US treasury bills as Smales (2016) suggests. Term spreads offer valuable insights into the yield curve, which shows the relationship between interest rates across different maturities. Specifically, the term spread assesses the disparity between long-term and short-term interest rates. Notably, CDS spreads are influenced by the term structure of the yield curve (Aman, 2019). Our approach is inspired by Smales (2016) where the term spread is used as a proxy indicator of market expectations concerning future economic conditions and potential credit risks. Fluctuations in term spreads reflect changes in market sentiment, expectations of economic expansion or contraction, and alterations in perceptions of credit risk (Aman, 2019).

To take the market volatility into account we incorporate the CBOE Volatility Index (VIX) which is an extensively utilized indicator of stock market volatility expectations (CBOE). The index is derived from calculations from S&P 500 index options and is continuously updated and shared by the Chicago Board Options Exchange (CBOE). It is commonly known as the “fear index” due to its ability to measure market sentiment regarding fear and uncertainty (CBOE; FRED). The VIX index is employed as a volatility proxy, reflecting the anticipated volatility of the S&P 500 stock market. Its application in similar research studies has been extensive (Smales, 2016), and the data for the VIX index is obtained through Eikon. The VIX index serves as a valuable benchmark of market volatility and risk aversion, and it has been utilized in previous studies to examine the connection between credit risk and market dynamics (Gonzalez-Perez 2013: Galil et al. 2014). In this study, we anticipate a positive relationship with the VIX index, indicating that heightened market volatility corresponds to elevated credit risk levels (Galil et al. 2014).

The final control variable in our study is the S&P 500 dividend to capture stock market health indicators. The S&P 500 dividend reflects the broader market performance. By considering the S&P 500 dividend in the analysis of banks' CDS, we gain insights into the exchange between dividend income and credit risk within the context of market dynamics and investor sentiment. This enables a comprehensive assessment of the factors influencing the pricing of CDS spreads for banks, and evaluating the creditworthiness and stability of banks in relation to their dividend performance (M. A., & Miljkovic, D. 2011).

4.3.3. Data descriptive

The following section presents the descriptive statistics for the sample period of March 2013 to March 2023. Table 1 presents descriptive statistics of monthly CDS spreads with a maturity of five years, ESG sentiment scores, and macro- as well as firm-specific control variables.

Table 1:Data Descriptive for all Observations

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
CDS spread	2299	72.06	34.496	19.82	448.79
ESG news sentiment	2299	-.014	4.186	-30.78	13.508

Control Variables

Macro Descriptive

Variable	Obs	Mean	Std. Dev.	Min	Max
VIX	2299	17.935	6.71	10.125	57.737
3-month T-bills	2299	.88	1.147	0	4.88
Term Spread	2299	1.286	.896	-1.18	2.97
S&P dividend	2299	1.864	.235	1.29	2.3

Firm-Specific Descriptive

Variable	Obs	Mean	Std. Dev.	Min	Max
Market CAP	2299	24.883	.994	21.915	26.942
Total Asset	2299	27.894	.623	26.129	28.951
Leverage	2299	25.123	20.553	4.775	147.631
Stock Return	2299	.28	6.899	-46.18	51.46

4.4 The model

To investigate the impact of our ESG sentiment score on a bank's credit risk, as measured by the *CDS spread*. To address this research objective, we use a panel data regression model that combines cross-sectional and time-series elements. Panel data analysis allows us to utilize information across multiple units observed over a specific time period. According to Brooks (2019), panel data regression is preferable because this approach offers several advantages. The first one is that panel data contains more information than purely time-series or cross-sectional data, enabling a comprehensive examination of dynamic behaviors across units over time. Secondly, it increases the statistical power from the inclusion of multiple units and time periods which provides a higher number of degrees of freedom, enhancing the power of statistical tests. Furthermore, panel data analysis can help mitigate issues related to multicollinearity that may arise in separate time-series regressions. Also, by employing this model, we can account for cross-sectional variation and examine changes in sector relationships over time. This approach also helps address the issue of omitted variable bias (Best & Wolf, 2013). Moreover, according to Brooks (2019) it combines cross-sectional and time series variations, resulting in greater variability and mitigating multicollinearity issues. However, it is important to acknowledge that panel data analysis may present challenges, such as analyzing nonlinear models and addressing cross-sectional dependence (Hsiao, 2007).

To conduct our regression analysis, we utilize the fixed effects estimator on balanced panel data using Stata SE 17.0. The fixed effects model is widely used in panel data analysis. While previous studies have predominantly used fixed effects models for firms in general, our focus is specifically on firms within the banking sector. To ensure data integrity and enhance the robustness of our regression analysis, we specifically selected companies with available *CDS spread* data for the entire sample period, reducing concerns related to missing data and enhancing the efficiency of our estimations. The panel data model can be represented by the equation:

$$Y_{i,t} = \alpha + \beta X_{i,t} + u_{i,t} \qquad (1)$$

In this equation, Y_{it} represents the dependent variable, α is the intercept term, β is a vector of parameters to be estimated, X_{it} is a vector of explanatory variables, and it is the composite error term and t stands for time and i for the bank. The composite error term can be decomposed into two components, $u_{i,t} = \mu_{i,t} + \varepsilon_{i,t}$, where $\mu_{i,t}$ represents the unobservable entity-specific effect and $\varepsilon_{i,t}$ represents the disturbance term. The entity-specific effect is time-invariant, while the disturbance term varies across time and entities. It should be noted that our panel data is balanced, meaning that firms have the same number of yearly observations. We check for both time-invariant and group-invariant fixed effects.

4.5 Statistical Tests

Before applying the regression model various tests have been conducted on the main sample as well as the subsamples. We used a Breusch-Pagan Lagrange Multiplier test to verify the suitability of the model for our panel data. The null hypothesis of this test is that there is no variance across entities. We reject the null hypothesis due to the p-value of 0.000 obtained for all our models. After confirming the appropriateness of the panel model, we will proceed to discuss fixed effects (FE) and random effects (RE) estimations. The Fixed Effects (FE) model and the Random Effects (RE) model are the two primary estimation methods for panel data. The RE model generally provides more efficient estimates than the FE model. However, for the parameter estimates of the RE model to be unbiased and consistent, certain assumptions must hold: a) the individual effect ($\mu_{i,t}$) is independent of the disturbance term ($\varepsilon_{i,t}$), and b) the composite error term ($u_{i,t}$) is uncorrelated with all the explanatory variables ($X_{i,t}$), indicating that the individual effects and disturbances are independent of the explanatory variables ($COV(\mu_{i,t}, \varepsilon_{i,t}) = 0$ and $COV(\mu_{i,t}, X_{i,t}) = 0$ for all i and t). If these assumptions are not met, the FE model is preferred (Bell et al. 2015).

To further evaluate the quality of our model for our panel data set, we conducted a Hausman specification test proposed (Hausman, 1978). This test evaluates the consistency of estimates obtained from the FE and RE models. Under the assumption that individual effects are uncorrelated with the explanatory variables, rejecting the null hypothesis indicates that the FE model is more suitable. In our study, the Hausman test yielded a significant p-value of 0.000 for all four models, leading us to reject the null hypothesis. Therefore, the FE model was selected as the optimal choice for our panel data set, ensuring consistent and unbiased estimators. This finding aligns with the FE approach adopted in previous research studies (Attig et al., 2013). The specified model we have chosen to use is outlined below:

$$CDS_{i,t} = \alpha + \beta ESG_{i,t} + \delta B_{i,t} + \omega M_{i,t} + \varphi FF + \varepsilon_{i,t} \qquad (2)$$

In this equation, CDS_t represents the change in the credit risk variable for an entity i at time t. The term $\beta ESG_{i,t}$ represents the sentiment variable at time t, capturing the $ESG_{i,t}$ factor's effect on the credit risk variable. $B_{i,t}$ denotes the bank-specific variables, $M_{i,t}$ represents macroeconomic variables, and FF represents the control factors. The coefficients α, β, δ, ω, and φ represent the estimated effects of the respective variables on the credit variable, while εt denotes the error term.

Before proceeding the analysis we also look for multicollinearity amongst our variables. Multicollinearity is a statistical concern that arises when the correlation between two or more independent variables becomes excessively high. The presence of multicollinearity leads to inflated standard errors for the affected variables and unstable coefficients that exhibit significant variation across different samples. Consequently, this undermines the reliability of the variables' statistical significance (Allen, 1997). After testing for multicollinearity as we could see in table 2 we do not find a particularly high level of multicollinearity in our sample. So we proceed to our estimation without any adjustments for multicollinearity.

Table 2: Pearson Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) CDS spread	1.000									
(2) ESG sentiment	-0.161	1.000								
(3) VIX	0.110	0.116	1.000							
(4) 3-month T-bills	0.055	0.064	0.042	1.000						
(5) Term Spread	0.116	-0.156	-0.290	-0.770	1.000					
(6) S&P dividend	0.301	-0.192	-0.169	-0.083	0.161	1.000				
(7) Stock Return	-0.104	-0.006	-0.153	-0.004	-0.003	-0.053	1.000			
(8) Market Cap	-0.347	0.054	-0.117	-0.014	0.079	-0.010	0.070	1.000		
(9) Total Asset	-0.274	0.016	0.036	-0.007	0.027	-0.078	0.006	0.607	1.000	
(10) Leverage	0.241	-0.056	0.182	0.030	-0.108	-0.056	-0.066	-0.719	0.037	1.000

Finally, a Breusch-Pagan Test (Breusch & Pagan, 1979) was employed to assess the presence of heteroscedasticity. Heteroscedasticity occurs when the variance of the error term is not constant, leading to unbiased estimators. Our results revealed significant Chi-squared values and p-values of 0.000 for all four models, indicating the rejection of the null hypothesis, which assumes normal distribution of the error term and confirms the presence of heteroscedasticity. To address this issue, robust standard errors based on Woolridge (2018) will be utilized in our fixed effects regressions and this will also correct any autocorrelation in our data.

5. Empirical discussion

5.1. Hypothesis 1

The results of the panel model on the relationship between the *CDS spread* and *ESG sentiment* (specified in eq. 2) for the entire sample of banks are presented in Table 3. The first row presents the coefficient and the significance level for *ESG Sentiment* on *CDS spread*, meaning the average impact of *ESG sentiment* on the *CDS spread* for all of the banks. Sequently, the following four columns show the coefficients and significance on the macro and firm-specific variables.

Table 3 reveals that *ESG Sentiment* exhibits a statistically significant effect on the *CDS spread* at the 5% confidence level. This finding indicates an inverse relationship between *ESG sentiment* and *CDS spread* across our entire sample of banks, thereby providing support for *Hypothesis 1*. This implies that as news sentiment increases (decreases), the credit risk decreases (increases). The estimated coefficient of *ESG sentiment* is (-0,312), that implies for every increase (decrease) of one unit in the *ESG sentiment* reduces (increases) the *CDS spread* by 31,2 basis points. This in turn implies that online public content related to ESG have risk mitigating effects on banks. Our findings are aligned, to some extent, with the expectations based on previous studies of credit risk (Barth et al 2022; Galetta et al 2022; Agnesa et al 2023; González-Fernández & González-Velasco 2020; Smales, 2016) and provides additional insight including that ESG sentiment online may have an effect on banks credit risk, albeit to a limited extent.

However, it is worth noting that other research su as Naumer & Yurtoglu (2022) found evidence of a negative relationship between ESG and the firm's financial performance score. Since our ESG score is derived from online sentiment, it could potentially be more closely linked to a reputational element capturing perceptions of ESG practices rather than the ESG factors reflected in conventional ratings. Also, according Galetta et al (2023) exposure to ESG risks is associated with greater visibility in the market and thus increases the vulnerability of some banks to the negative effects generated by non-compliance with ESG principles.

Table 3: Whole Sample - Fixed Effect with Robust Stand

CDS spread	.
ESG Sentiment	-.312**
	(.129)
VIX Index	.661***
	(.1)
3-Month T-bills	14.991***
	(.776)
Term Spread	22.976***
	(1.074)
S&P dividend	46.572***
	(2.778)
Stock Return	-.095
	(.089)
Market Cap	-34.384***
	(3.667)
Total Asset	34.346***
	(6.812)
Leverage	.47***
	(.098)
R-squared	0.406
Number of observation	2299
Prob > F	0.000

*** $p<.01$, ** $p<.05$, * $p<.1$

Furthermore, when examining the macro variables we observe that changes in the *VIX Index* have a positive impact on the *CDS spread* which indicates that the higher volatility in the market the higher the *CDS spread*, as expected. However, the *3-Month T-bills* yield and *Terms Spread* and *S&P dividend*, are positively associated with changes of the CDS spreads, implying that an increase (decrease) in *3-Month T-bills* yield and *Terms Spread* and *S&P dividend*, would increase (decrease) CDS spread. These findings do not align with the previous study that suggest decline in CDS spread due to increase in *3-Month T-bills* yield and *Terms Spread* (Smales, 2016). However, worth noting is that Smales (2016) studied the news sentiment in general and not new sentiment specifically related to ESG. Also worth mentioning is that the correlation between CDS spread and *3-Month T-bills* yield and *Terms Spread* could be depending on overall market sentiment (Hasna et al. 2021). One could argue that in an improving economy leads to higher competition and banks are willing to expose themself to more risk and liabilities through more lending by the banks (Boahmah et al. 2021). Which allows increasing the uncertainty of the future thus why CDS spread for banks goes up. Although this pattern may not hold for all firms. The same logic could be applied for the relationship between CDS and S&P dividend, it is quite complicated and it could be affected by overall market sentiment.

Regarding firm-specific variables, *Stock Return* and *Company Market Cap* both have a negative impact on the *CDS spread*, while *Leverage* has a positive effect, as anticipated. A higher return on stock and bigger market cap potentially lead to lower CDS spread (Smales, 2016), and the lower leverage decreases *CDS spread* as the banks creditworthiness becomes riskier when their capital structure takes on more debt. This is because the probability of default decreases (Smales, 2016). Unexpectedly, in our result the *Total Assets* variable had a positive effect on the *CDS spread*, in contrast to non-financial firms that have a negative relation with *CDS spread*. One could argue that the higher asset under management could potentially make banks more prone to high withdrawals under uncertain time and pessimistic view of withdrawal can consider higher assets under management more risky (Di Febo et al., 2015).

5.2 Hypothesis 2

The outcome in table 4 shows the subsamples of positive and negative ESG sentiments. The *ESG sentiments* with positive scores had an insignificant effect on the *CDS spread,* while the negative *ESG sentiment scores* are significant at the 1% level. Notably, the coefficients for negative ESG sentiment scores were highest amongst all other samples, indicating a more pronounced effect on CDS spread. The results indicate that a change of +1 score in negative sentiment would increase CDS by 103.3 basic points. Which implies a stronger change in CDS spread. On the other hand, the positive sentiment data does not exhibit any significance. All macro and firm-specific variables follow a similar relationship as table 3.

The findings clearly indicate that negative sentiment samples have a more significant negative effect on CDS spreads. This suggests that CDS spreads react more assertively to negative news. Conversely, the CDS pricing market remains uncertain about the impact of positive news. Our findings are aligned with previous research that has shown that negative news is more informative and gets a more explosive reaction from the CDS market (Riodarn et al, 2013).

As A. Smales (2016) emphasizes the CDS spread reacts more on the news sentiment, rather than the mere presence of relevant news. This asymmetric sentiment implies that negative news has a stronger effect on CDS spreads compared to positive news (Smales (2016)). Our findings support the existing literature on asymmetries of new sentiment, emphasizing the importance of considering the direction and nature of sentiment in analyzing its impact on credit spreads. Based on the results, we do not reject the hypothesis that the ESG sentiment and credit measures are asymmetric and that negative ESG sentiment induces a more significant response than positive ESG sentiment.

Table 6: Sub-sample asymmetric sentiment - Fixed Effect with Robust Stand

CDS spread	Negative	Positive
ESG Sentiment	-1.033***	.22
	(.27)	(.372)
VIX	.268	.75***
	(.184)	(.117)
3-month T-bills	14.491***	15.736***
	(1.443)	(.922)
Term Spread	21.938***	23.709**’
	(1.798)	(1.321)
S&P dividend	62.634***	40.983***
	(5.638)	(3.212)
Stock Return	.157	-.172*
	(.156)	(.103)
Market Cap	-51.157***	-27.196***
	(7.035)	(4.449)
Total Asset	29.242**	33.709***
	(12.32)	(8.177)
Leverage	.631***	.566***
	(.206)	(.11)
R-squared	0.432	0.428
Number of observation	798	1173
Prob > F	0.000	0.000

**** p<.01, ** p<.05, * p<.1*

5.3. Hypothesis 3

Table 4 presents the panel regressions result of relationship between *ESG sentiment* and changes in the *CDS spread* for the regional subsamples. The European banks follow a similar result as the regression on all of the banks in our sample, however, the sample of US banks did not have a statistically significant result between *ESG Sentiment* and *CDS spread*.

Table 5: Sub-sample of European and US - Fixed Effect with Robust Stand

CDSspread	European	USA
ESG Sentiment	-.634*** (.191)	-.085 (.109)
VIX	.329** (.146)	.514*** (.093)
3-month T-bills	22.265*** (1.149)	6.602*** (.681)
Term Spread	34.034*** (1.686)	15.961*** (.847)
S&P dividend	59.583*** (3.675)	45.743*** (3.464)
Stock Return	.152 (.263)	-.147*** (.051)
Market Cap	-84.584*** (7.874)	-46.301*** (6.739)
Total Asset	6.077 (10.606)	107.707*** (9.22)
Leverage	-.145 (.157)	-1.193** (.583)
R-squared	0.687	0.489
Number of observation	1452	847
Prob > F	0.000	0.000

**** p<.01, ** p<.05, * p<.1*

European banks demonstrate a negative relationship at the confidence level of 1%, similar to prior research, as discussed above. European banks show a higher coefficient (-0.634) and significance level than the regression with all banks (-0,312). One indication could be that European banks experience a bigger risk mitigation effect than the US which could potentially be attributed to ESG factors being priced in the credit market to a larger extent for the banking sector in Europe as previously discussed literature would suggest. Europe has implemented varios ESG frameworks such as Corporate Sustainability Reporting Directive and Sustainable Finance Disclosure Regulation and they are considered to be global leaders in implementing (Bruno & Lagasio, 2021), thus why ESG sentiment score shows more significance in Europe and none in the US.

However, since the US banks have an insignificant result we lack evidence to support our second hypothesis and can not find any evidence of regional differences for the relationship between *ESG Sentiment* and *CDS spread* in our sample. Moreover, the regional results may cast a shadow on our regression outcomes for our entire sample of banks, given that the original sample significance level and coefficients lie between the European and the US subsamples.

The macro variables have a similar pattern in both subsamples where positive relationships exist between every macro variable and the *CDS spread*. On the other hand, European firm-specific variables do not show any significance except for the bank's market cap, where a negative relationship with the *CDS spread* is observed. The firm-specific variables in the US subsample show significance. negative relationship between stock return and market cap with *CDS spread* and positive with total asset under management.

5.4 Hypothesis 4

Table 6 shows the result for the panel analysis conducted on subsamples corresponding pre-covid-19 and covid-19. The results indicate that the *ESG sentiment* before the Covid-19 pandemic had a significant negative impact on CDS spreads at a 1% significance level. However, the result for the following period, indicates a positive relationship at the 5% significance level between *ESG sentiment* and the *CDS spreads*. This shift may be attributed to overall market uncertainty during covid-19, which led to CDS market having a positive reaction disregard to ESG sentiment. Additionally, other macroeconomic factors such as energi prices and lockdown could influence the CDS spread price. Which led to investors fearing the future of the market and expected a longer lockdown and increase in prices (B. Daehler et al. 2021). As for the macro variables in pre-covid- 19 subsample we observe a similar relation as table 3, And firm-specific variables (*Market Cap*, *Stock Return* and *Total Asset*) have negative relationship leverage positively and with CDS as expected. A study by Apergis et al. (2022) showed that the severity of the pandemic had a significant influence on CDS spreads.However, their model also indicated uncertainty surrounding the pricing of CDS spreads in times of distress. Our finding indicates that ESG news sentiment has a positive relationship with CDS under covid-19, which could imply to a certain degree of ignorance towards both positive and negative news. In conclusion, we cannot reject our hypothesis and rely on our results, which suggest that under uncertain times and different time periods, such as various business cycles, the relationship between ESG news sentiment and CDS spread can be uncertain and challenging to explain..

Table 6: Sub-sample of Pre Covid-19 and Covid-19 - Fixed Effect with Robust Stand

CDSspread	Pre Covid-19	Covid-19
ESG Sentiment	-.446***	.843**
	(.114)	(.375)
VIX	.662***	1.699***
	(.212)	(.181)
3-month T-bills	10.28***	23.262***
	(1.68)	(1.099)
Term Spread	17.705***	24.9***
	(1.514)	(2.614)
S&P dividend	129.73***	-19.466**
	(8.343)	(8.297)
Stock Return	-.222*	-.119
	(.119)	(.096)
Market Cap	-14.67***	-26.122***
	(4.955)	(6.855)
Total Asset	-27.126***	-87.82***
	(9.264)	(14.448)
Leverage	1.356***	.744***
	(.133)	(.146)
R-squared	0.535	0.577
Number of observation	1436	673
Prob > F	0.000	0.000

*** *p<.01,* ** *p<.05,* * *p<.1*

5.5 Discussion

The aim of our research was to investigate the effect of ESG sentiment on changes in CDS spread in the banking sector. Previous studies have mainly focused on firms in general when examining the effects of ESG ratings. Based on previous research, we formulated the hypothesis that there is a relationship between ESG sentiment and firm CDS spread in the banking sector, which causes some uncertainty due to the different nature of the firms we use in our sample. The main take-away from previous studies on firms in general is the rationale that ESG sentiment has a negative effect on credit risk which we did observe indications of in our study.

Furthermore, our results gave small indications of the European banking sector being more influenced by ESG sentiment than the US. However, there was not enough evidence to support a correlation in the US banking sector making the regional comparison tough. Furthermore, we explored how different time periods can affect the reaction to ESG sentiment by studying the periods before, and during, *COVID-19* pandemic. The results suggested negative correlation between ESG sentiment and CDS spread pre-covid-19 period, while during uncertain times (covid-19), the data showed a positive correlation between ESG sentiment and CDS spread. However, it is worth noting that our Covid-19 sample covered a relatively small time period (3year), which may have influenced the outcome of our results. Conducting further studies with a larger post-COVID-19 time period could potentially yield more robust results.

Finally, we also investigated the magnitude of sentiment asymmetry by examining the correlation between negative and positive ESG sentiment score and CDS spread. The results indicated that negative sentiment has a stronger inverse relationship with CDS spread compared, on other hand we did not find significance on our positive sample. Regarding the effects of negative and positive sentiment, it is evident that negative sentiment has a greater impact on CDS spread. This can be explained by the rational behavior of markets, where negative sentiment is adopted and lingers longer compared to positive sentiment. This is reflected in our results. Positive news sentiment often carries less weight than negative sentiment. It should be noted that our observation sample differed in size considerably between positive and negative sentiment, with a higher occurrence of negative sentiment. Conducting further studies with a larger sample or equal proportions of positive and negative sentiment observations could potentially yield more interesting findings.

Throughout our study, we obtained interesting results that contribute to the understanding of how ESG is priced in credit risk markets. However, there were limitations in terms of the time period covered. Our study primarily focused on ESG-related news sentiment in the digital world, such as online news articles and business press. The study could be expanded by including all news sources to ensure long term consistency in the research. We were restricted to using data from the period after 2013 since there was a considerable lack of data on the internet prior to that date.

Another suggestion for further studies would be, investigating the possibility of forecasting the CDS spread with help of ESG news sentiment. We used a panel data regression with fixed effect but we could further use a (VAR) vector autoregression model to study if CDS spread effects ESG sentiment and if future prediction CDS could be relied on ESG sentiment. Our study explores a new area of ESG sentiment and its effects, with a focus on the financial sector, which has not been extensively studied in previous research. Our interest originally came from recent bank turmoil and how the internet allows for information to spread faster than ever. However, the study could be further extended to examine the effect of internet news sentiment on banks' CDS. Due to the limited research in this area, we encountered some theoretical limitations. Previous literature on similar topics was combined to the best of our ability into a new study. Our findings could hopefully be used for inspiration of new credit risk factors to consider and how to understand ESG sentiments impact in the banking sector.

6. Concluding remarks

While previous studies on ESG factors, news sentiment and credit risk have primarily focused on firms in general our research aimed to investigate the effect of online ESG sentiment on changes in CDS spreads and specifically within the banking sector. We present empirical evidence demonstrating that online sentiment surrounding ESG factors significantly influences the Credit Default Swap (CDS) spread of banks. By identifying the relationship between ESG sentiment and CDS spread, we contribute to the ongoing investigation for alternative data sources to incorporate in credit risk assessment and to find predictive abilities of online ESG sentiment in the credit market.

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Appendix A

List of Banks

Number	Name	Country
1	Bank of America	US
2	Barclays PLC	United Kingdom
3	BNP Paribas	France
4	Citigroup Inc	US
5	Commerzbank AG	Germany
6	Crédit Agricole S,A,	France
7	Credit Suisse Group AG	Suiss
8	Deutsche Bank	Germany
9	HSBC Holdings plc	United Kingdom
10	ING Groep N,V,	France
11	JPMorgan Chase & Co	US
12	Morgan Stanley	US
13	Skandinaviska Enskilda Banken AB	Sweden
14	Société Générale Société anonyme	France
15	Standard Chartered PLC	United Kingdom
16	The Goldman Sachs Group	US
17	U,S, Bancorp	US
18	UBS Group AG	Switzerland
19	Wells Fargo & Company	US