Chair CANDRIAM/KEDGE
Finance Reconsidered: Addressing Sustainable Economic Development

"*CLIMATE: NO NEWS IS GOOD NEWS?*"
ESG & FIXED INCOME
Climate Sensitivity in EURO Corporate Bonds

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List of Abbreviations

3FF: Fama-French Three-Factor Model

5FF: Fama-French Five-Factor Model

OAS: Option Adjusted Spread

CDP: Carbon Disclosure Project

CRF: Credit Risk Factor

DRF: Downside Risk Factor

DTS Duration times spread.

ESG: Environmental, Social, and Governance

ICE BofAML: Inter-continental Exchange Bank of America Merrill Lynch

IG: Investment Grade

GHG: Greenhouse gases (carbon dioxide, methane, nitrous oxide, and ozone)

MSCI IVA ESG: MSCI Industry-Adjusted-Score

MSCI: Morgan Stanley Capital International

LRF: Liquidity Risk Factor

TEG: Technical expert group on sustainable finance

TRACE: Trade Reporting and Compliance Engine

HY: High Yield

Section 1

Introduction

This paper examines whether climate risks are priced in Euro-denominated corporate bonds. Motivated by the growing trend of considering Environmental, Social, and Governance (ESG) in investment strategies, this paper reviews current ESG approaches in fixed income. More specifically, it draws on the debate on factor investing in implementing a procedure able to hedge climate change risks in the European market.

One noticeable trait among fixed-income assets is the lack of systematic methodologies for portfolio construction. The challenge lies in incorporating the complex structure of bonds to handle macro-economic variables, unexpected defaults, and a changing climate. Hence, this study considers common risk factors that play on the corporate bond markets (Credit Risk, Liquidity Risk and Downside Risk) and pairs them with factor-related exposures of environmental opportunities and concerns. The cross-sectional view identifies potential candidates for investments as well as climate change hedges.

This research further shows that there is evidence of jumps during periods of worldwide climate conferences. The study presents evidence that aggregated ESG and E pillar have a negative relationship with bond spreads. Similarly, higher climate concerns increase bond spreads; however, higher climate opportunities does not show a significant positive relationship. To manage climate risks at the portfolio-level, concerns are priced but opportunities not.

Give the rise of ESG, from exclusion to full ESG integration, investors enrich the profile of their investments through fundamentals paired with extra-financial analysis. More often than not, the extra-financial analysis depends on ESG scores by external providers. ESG scores summarize information related to positive or negative externalities. With no market consensus on ESG scores, and limitations of the scope of CO2 emissions, it is a real identification challenge. The challenge becomes even harder for corporate bonds because ESG is tailor-made at the firm-level, not at the bond-level. Although ESG focuses primarily on equities, it has a lot of undiscovered benefits for fixed income. For both asset classes, ESG can help identify environmental strengths and/or risks, which are crucial for capital conservation. Instead of capturing potential excess returns as in equities, fixed income focus on mitigating downside risks. Compared to the wide range of ESG strategies in the equity market, fixed income research has lagged behind, until recently.

A glimpse into the future of emissions

While anticipating stricter climate-related regulations, some investors are already using models to internalize ESG externalities directly into asset allocation, for instance, stress-tests or in-house ESG scoring models. For the moment, there is no clear academic consensus whether ESG is integrated in the market neither for equities, nor fixed income. For the purpose of climate benchmarks, public companies engage to report their GHG emissions. These are measured by scope 1 (direct), 2 (indirect), or 3 (value chain). Scope 3 emissions are significantly harder to estimate than Scope 1 or even Scope 2, whereby double counting and life-cycle specifications affect significantly the estimates. The Technical expert group on sustainable finance (TEG) suggests the need to conduct firm-specific analysis for the Scope 3. These measurements remain a priority, giving the imminence of climate change. The majority of green investors monitor the carbon footprint of their portfolios, with this in mind, they try to limit their portfolio GHG emissions, exclude intensive CO2 sectors, and reduce brown assets. However, there is still no consensus among optimal climate strategies. The divergence between ESG scores among the raters and the limitations of the CO2 scopes, complicate the recommendations for these benchmarks.

The forward-looking implementation of stricter green policies will affect the valuations of certain assets, known as stranded assets. The identification of these stranded assets is important to financial risk management in order to avoid economic loss after an asset has been converted to a liability. The main risks of the stranded assets are physical regulatory, or transition risks. The losses from physical risks come from the higher frequency of extreme weather events and natural catastrophes damages. While physical risks occur sporadically, exposed assets are affected by policy changes and shift in the market preferences. Hence, the economic consequences of these stranded assets are likely to worsen over time. One strategy for portfolio protection is to sell those stranded assets, and at the same time reducing the exposure to CO2. So, the central question remains: how to identify the stranded assets. Again, there is a question of what type of climate risk exposure is captured by ESG. Specifically, ESG may more closely capture regulatory risks than physical risks. Exploring different climate risks (physical, transition or regulatory) constitutes an interesting starting point for this research.

Disclosure is central, but yet disclosure will not answer the question of portfolios allocation. Due to self-reporting and measurement biases, ESG integration is not yet the optimal solution. The search for the winning ESG strategy continues among investors, for equities as well for fixed income.

Due to the stakes of global warming, the firm's carbon footprint has attracted mainstream interest. Consequently, the public expects from corporations a new set of metrics on how they should balance their financial and non-financial capital to reduce such emissions. Governments being in debt and the private sector feeling resource-constrained, people hope that corporations will help solve challenges ranging from income inequality to climate change. Thus, investors are increasingly allocating capital in a manner that rewards good environmental behaviour, and it's aligned with the climate regulations (i.e. 2C initiative.)

More exposed companies tend to have less ability to borrow money from banks at a lower price. Notably, these limitations increased after the Paris Agreement. Nowadays, the emission reduction pledges are being tested under pandemic conditions. The pandemic has prompted significant shifts in the economy, moving consumption and consumer behaviour. As economic downturns appear globally, firms facing uncertain demand need to rely on other ways to raise capital, such as the reliance on debt markets.

In addition, the diverse scope of debt instruments, issuers, and maturities requires specific analysis for each instrument, grade and rating. Thus, attributing the firm-level ESG score to all bonds issued of a given company can present additional limitations. While each company is directly linked to their stock, a company can issue numerous bonds, heterogeneous in nature. For fixed income, this can become a problem since, companies issue several bonds of different duration and configurations. Thus, including a climate sensitivity index, can help address these issues.

This research tries to shed light on the affinity of climate and bond returns. To account for climate sensitivity, the E dimension must be unbundled to identify environmental concerns and strengths due to climate change.

A significant limitation is related to ESG data transparency. Currently, the leading data providers (Bloomberg, MSCI, ASSET 4, Sustainalytics, Vigeo) offer ESG data of several listed companies. However, there is a divergence among ESG scores (Barth, Hübel, and Scholz, 2019). Their findings reconcile mixed evidence on ESG ratings and reinforce the notion that the lack of consistency in ESG ratings could distort risk-return trade-offs and the firm's profile. Researchers often use average ratings, across all ESG providers to create market consensus. In addition, the diverse scope of debt instruments, issuers, and maturities requires specific analysis for each instrument, grade and rating. Thus, attributing the firm-level ESG score to all bonds issued of a given company can present additional limitations. While each company is directly linked to their stock, a company can issue numerous bonds, heterogeneous in nature. For fixed income, this can become a problem since, companies issue several bonds of different duration and configurations. Thus, implementing a climate sensitivity analysis, can help address the ESG issues, from an external perspective. We discuss such limitations with more detail in Section 3.

1.1 Outline

The paper is structured as follows. The introductory section provides an overview and background of the current ESG practices, and presents the motivations, and key concepts of the study. Section 1.2 surveys existing literature in relation to factor investing and ESG-investing in corporate bonds. Section 2 presents the empirical application. Section 3 discuss the results, limitations, and concludes.

1.2 Literature Review

Section 1.3 starts by addressing the factor investing framework in fixed income. Factor models convey on common sources of risks to explain bond returns. Subsequently, these models are adapted though an ESG lens. Then, the following part focus on the climate change sensitivity of assets. To shed light on the relationship between climate and bonds, this study builds on these models to conduct the empirical research. By considering both common risk factors of corporate bonds, Environmental scores, and climate sensitivity, it is possible to disentangle the relative impacts of climate risks at the portfolio-level. This paper contributes to this literature by analyzing the effect of climate on bond portfolios.

1.3 Factor Investing, Corporate Bonds & ESG integration

In practice, there are two sources of potential risks in bond management. The first is related to interest rates forecasting, where duration and convexity play a crucial role for bond price valuation. The second is the identification of relative mispricing, with the misalignment of premiums and prices. The starting point of this literature is to identify systematic fixed income strategies that open the floor for the integration of ESG metrics, being ESG a mispricing signal or a friction for bonds markets.

To define what a risk factor is, Ang (2014) compares the source of risk premia to food nutrients. He explains that *"factors are to assets, what nutrients are to food"*. Where each type of food is a bundle of nutrients, each asset is composed of a bundle of factors. The explanation behind is that factors determine the risk premium, not the asset class. For the reason that portfolios contain groups of stocks, sovereign and corporate bonds, or even funds of funds, these contain correlated levels of equity risk, volatility, interest rate risk, and default risk.[1] Implicitly, the bond market share common determinants related to stocks characteristics, which capture common variations of bond and stock returns, as well.

Despite the success of factor-investing for equities (Harvey, Liu, and Zhu, 2016), research still lags for fixed income (Houweling and Van Zundert, 2017). The literature is not yet consolidated, especially for corporate bonds because there are additional constraints due to data availability, non-linear structure of bonds, and illiquidity (Dynkin et al., 2007).

Originally, Fama and French (1993) define the term premium (TERM) and default premium (DEF) for corporate and sovereign bonds. For TERM, changes in the risk-free interest rate are the main drivers of this premium. However, it is possible to remove the TERM premium using returns in excess of duration-matched risk-free rates. Since interest rates are independent, the focus shift to the default premium, driven by changes in credit spreads (Bektić et al., 2019). Additional studies focus on corporate bond anomalies, implementing the predictors for equity returns in a corporate setting. They point out that size, value, profitability and momentum factors play a role in bonds too (Bektić et al., 2019; Ilmanen et al., 2004; Ang and Ulrich, 2012). Still, there is no clear evidence whether these factors are the same between the US

1. In a deep sense, factor regressions tell how the right hand (returns) variable is formed, from expectations of the left hand variable (factors).

and European IG markets. Market segmentation suggests that IG bond returns cannot be fully explained using traditional factors (limited to equity characteristics). The Fama-French equity risk factors are country specific and market specific. Hence, local factors specific to the country, and market provide a better explanation of the variation in returns than the one-size-fits all factors (Griffin, 2002).

Previous studies concentrate on systematic risks (from the market as a whole), which includes multi-asset portfolios. In related (but still limited) literature, the following studies consider a systematic risk unique to corporates. From an empirical perspective, this framework opens the door towards the identification of related factors in corporate debt. Thus, when considering the construction of bonds-only portfolios, risks specific to bonds need to be studied. Even if, the risk can be diversified by investing in other assets.

Due to the specific characteristics of corporate bonds, some risks cannot be explained by traditional factors. Bali et al. (2020) investigate the determinants of corporate bonds returns at the cross-sectional level. They analyze Trade Reporting and Compliance Engine (TRACE) data from July 2002 to December 2016, and find that downside risk, credit risk, and liquidity risk have significant risk premia for bonds. Credit risk is the strongest predictor of future bond returns. Thus, as stated by it is important to identify common risk factors based on corporate bonds risks characteristics (Downside, Credit, and Liquidity) rather than relying on stock market factors (Fama-French) or aggregate bond market factors like DEF, TERM.

ESG Integration

For fixed income, the main sustainability scene relates to green bonds (Zerbib, 2019; Flammer, 2021; Hachenberg and Schiereck, 2018), their drivers of growth, and impacts (Tolliver, Keeley, and Managi, 2020). But still, the green bond market represents a small portion of the total fixed income market, roughly a 6.1% of the of global debt market (Moodys, 2020).

A growing body of recent literature gives attention on the implications of ESG from a risk factor perspective. This section ends with some papers for which their research aims to capture ESG risk factor exposures in corporate bonds. The main distinction between the above mentioned financial-only factor literature from the ESG literature is the inclusion of extra-financial dimensions in asset models.

In a pioneer study, Polbennikov et al. (2016) explores the Barclays MSCI Corporate Sustainability Index, since its inception in 2007 until 2015. Using the Barclays U.S. Corporate Index as benchmark and merging MSCI ESG scores at the issuer-level, the authors find that higher ESG scores have higher credit ratings, lower average spread, lower DTS, and lower liquidity cost. While aggregated ESG shows positive performance from 2007 to 2015, ESG separated by pillars shows mixed evidence. Governance appears the strongest contributor, but Environmental and Social scores show weaker significance. They infer that ESG follows the market trend performance, with evidence of reversal during the 2008 crisis, where risk aversion increased. In times of distress, investor preferences might want to concentrate on financial performance only, and then sustainable issues. In contrast, when they apply a SRI filter to exclude companies involved in controversial activities, there is a reduction of average returns, and a spread increase.

Slimane et al. (2019, 2020) explore the asset pricing implications of ESG in fixed income markets. The first study focus on Sovereign fixed income securities, while the latter study focus on corporate bonds. In this second study, they explore the ESG implications on the Inter-continental Exchange Bank of America Merrill Lynch (ICE BofAML) IG and Global HY Indexes, from 2009 to 2019. Their results show market segmentation between EUR IG and USD IG. Spread regressions show lower cost-of-capital for issuers with better ESG ratings. There is a positive correlation between ESG and credit ratings. But this might also point out that credit rating agencies already incorporate extra-financial risks into their scoring models, thus potential double causality issues might arise.

Previous empirical studies indicate that better ESG is associated with higher credit ratings. In terms of corporate bond spreads, Menz (2010) finds evidence that higher ESG have lower credit spreads. Barth, Hübel, and Scholz (2019) indicate that higher ESG ratings mitigate credit risks of U.S. and European firms from 2007 to 2019. A one-standard-deviation improvement in ESG ratings reduce CDS spreads by 4%/8%/3% of low, medium, high ESG firms. However, the risk mitigation effect has an U-shaped form across ESG quintiles.

To sum up, credit risk models can be improved when incorporating ESG, resulting in more efficient risk management and potential performance benefits. Hence, evidence shows the relationship of CO2 footprint and credit risk, and the association of ESG with credit quality. Thus, it is important to control for the exposure to climate risks while analyzing bond returns. However, controlling for ESG may reflect components related to the firm-level and not due to common variation in the cross-section of bonds returns.

Capasso, Gianfrate, and Spinelli (2020) transpose the credit risk to climate risk, by adapting the Merton (1974) structural model with $CO2$ emissions. They investigate the relationship between emissions and distance-to-default. Findings show significant evidence that a greater exposure to climate risks affects the creditworthiness of bonds. The distance gets smaller with higher levels of CO2 emitted. An increase of 1% in CO2 emissions lower the distance to default by -0.18. Using a difference-in-differences approach, they find that after the Paris agreement, an increase in 1% in CO2 emissions affect negatively the distance-to-default by -0.3. The role of the Paris Agreement is seen as an exogenous shock that affected the perception of corporate debt risk. Barth, Hübel, and Scholz (2019) see the Agreement as a turning point, where only after, climate change become relevant to prices and risk.

1.4 Climate Change, News & Sensitivity

This section 1.4 relates to research associated with climate change sensitivity, sentiment and news. We discuss in detail the implications in relation with bond returns.

To the extent that the climate change capture systematic risk factors that have not yet been fully priced. Climate news might include the possibility of changes in the regulatory business environment, tightening of ETS, stricter carbon taxes, and constraints of GHG. In such cases, assets with high ESG scores could signal less risk exposure for these changes. The results might lead to portfolios containing less stranded assets. Stranded asset should be avoided at stakes of the climate. However, a systematic identification of such assets is quite difficult.

Some studies have begun to shed light on the climate sensitivity of such assets concerning environmental issues, climate change news, and climate sentiment to assess its impact on asset prices.

Engle et al. (2020) implements a dynamic strategy that hedges news about climate change which pays off in the event of a future climate disaster. For the portfolios construction, they create a "climate" factor mimicking measure. Based on coverage of The Wall Street Journal (WSJ) articles, the climate index counts the number of articles related to climate change. Using text-based analysis, the index measures the extent to which WSJ articles overlaps with climate change glossary. Coverage of climate news has a positive trend over time and around acute global climate events. [2]. The authors use ESG scores from MSCI and Sustainalytics, to have a firm-level environmental profile. In the same fashion as Fama and French (1993), they construct the portfolios using the cross-sectional value and size factors.

Similarly, Bessec and Fouquau (2020) measure the growing concern about environmental issues and assess its impact on stock prices. The study reflects news sentiment from the WSJ coverage regarding environmental issues and investigates their influence on the S&P500 constituents. They find a significant impact on stock returns in the sectors more exposed to environmental risks. At the firm-level, this impact is also linked to their environmental performance. The lexicon for the semantical analysis differs from one study to other. While Bessec and Fouquau (2020) includes all environmental news, Engle et al. (2020) is limited to climate change issues only. To focus specifically on negative climate news, Engle et al. (2020) complements the index with the services of the data analytic vendor Crimson Hexagon (CH) which enables a sentiment analysis of positive or negative news. [3]. In a similar manner, Brøgger and Kronies (2020) construct a text-based sentiment measure and create a index based on Google searches for *Climate change*[4]. The findings show that portfolios sorted on ESG are useful in hedging recessions.

As well, these studies provide interesting results on how climate change affects asset prices, bond prices are not considered. In all cases, the question remains as to what type of climate risk these indices capture. Precisely, they may more closely capture regulatory risks than physical risks or transitional risks.

Climate sensitivity of Corporate Bonds

Huynh and Xia (2020) applies the WSJ index (Engle et al., 2020) to study whether climate change news risk is priced in corporate bonds. The authors estimate the climate change news beta from the monthly 60-month rolling regressions of bond excess returns on WSJ. Furthermore, the results suggest that bonds with higher exposure to climate change earn lower future returns. These results go hand in hand with the asset pricing implications of the demand for bonds with a high potential to hedge against climate risk. What this means is that when investors are concerned about climate risk, they are willing to pay higher prices for bonds issued

2. Available online at J. Stroebel's website: http://pages.stern.nyu.edu/~jstroebe/

3. Other studies also rely on newspaper articles to create proxies focusing on different dimensions; for instance, Baker and Wurgler (2012) construct the Geopolitical Risk index.

4. Available online at A. Brøgger's website: http://andreasbrogger.com/#data

by companies with better environmental performance.

Further robustness checks show economic significance of the coefficients. The sensitivity of Climate Change of -0.03 indicates that a one-standard-deviation increase in the climate change news beta is associated with a decrease of 12.60% relative to the sample mean of excess returns. Compared to Bai, Bali, and Wen (2019)'s DRF, the estimated coefficient of 0.09, indicates that a one-standard-deviation increase in DRF is associated with an increase of 51.34% relative to the sample mean. A smaller effect of Climate change sensitivity goes along with the Cornell and Damodaran (2020) claims that the markets incorporate weakly climate risk into asset prices.

Section 2

Empirical Application

Section 2 describes the empirical application. It starts with data definitions and methodological procedures used to construct the factors, followed by an exploratory analysis of ESG and credit. Then, it shift to the construction of the Climate Awareness index, with the respective climate and carbon exposures based Climate Change news. Robustness checks verify this relationship with worldwidenews and Google Searches[1]. It ends with the portfolio implementation and spreads regressions.

Objectives:

- To offer empirical evidence that climate has meaningful effects in the European corporate bond market.
- To analyze differences between Climate Concerns and Climate Opportunities.
- To provide more complete picture of the link between spreads and ESG, by regressing bond-level spreads on different climate metrics.

The playing field

The data used for the study is made up of end-of-month bond prices over the period December 2015 to December 2020. These bonds are constituents of the Markit IBOXX EURO Corporate Index. The methodological procedure follows closely Bai, Bali, and Wen (2019) on the construction of factors; and Huynh and Xia (2020) on the implementation of climate news on corporate bonds.

Inspired by Bai, Bali, and Wen (2019), we construct CRF, LRF and DRF risk factors[2]. Climate sensitivity is determined based on European and Worldwide newspapers' climate coverage[3]. We can infer on climate riskiness by examining the covariates between the number

1. (Brøgger and Kronies, 2020) define in more detail their implementation
2. Some filters as suggested (Bai, Bali, and Wen, 2019) are already taken into consideration by Markit before the inclusion into the index.
3. The database was made public by the Media and https://scholar.colorado.edu/concern/datasets/nz806067tClimate Change Observatory (Media and Climate Change Observatory (MeCCO))

of climate news and bond prices, those that become more attractive if the number increases, or vice versa. We assume that gaps between regional and global news untwine climate risks. From a global perspective, climate coverage reveals transitory risks reflecting a change in aggregated demand. From a regional perspective, gaps in coverage mainly represent those regulations in Europe that address climate change.

The appendix A.1 presents additional statistics summaries, GICS sector breakdown, and performance overview.

2.0.1 Bond Measures

Bond returns

The calculation of the indices is based on bid prices. In the event that no price can be established for a particular security, the index continues to be calculated based on the last available price[4]. This might be the case in periods of market stress, or disruption as well as in illiquid or fragmented markets.

Following Bessembinder et al. (2008), we calculate monthly corporate bond returns as follows:

$$r_{i,t} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1$$

where $P_{i,t}$ is the Price of bond i at the end-of-month t, $A_{i,t}$ is the accrued interest, and $C_{i,t}$ is the coupon payment, if any. The excess return is defined as the difference between the bond return and the risk-free rate, $r_{f,t}$, which is based on JP Morgan 1M EUR Cash index. Monthly excess of return are calculated as $R_{i,t} = r_{i,t} - r_{f,t}$.

Bond market Beta

The market returns of Markit IBOXX EUR Corporates Index differs substantially between $R_{i,t}$, because of their weighting scheme. Total index returns are Value-Weighted, and the returns of the sample are calculated as Equally-Weighted[5]. $(MKTBond)$ is calculated to the equally-weighted average return of all corporate bonds in our sample in excess of $r_{f,t}$.

Credit Ratings

Bond-level ratings synthesize the information on both the issuer's financial condition, operating performance, and risk-management strategies, along with specific bond characteristics

4. In the US, there are differences between TRACE trade prices versus Lehman quote data. From one side, TRACE prices equal quotation midpoints, where most academics would use the midpoint of the spread as the fair price. On the other side, Lehman prices are quoted as bid prices, where bids reveal the preferences from the highest willingness to pay from investors at the time of the quote. Most US studies use TRACE, which accounts with additional transaction data.

5. B discuss the arguments behind the EW choice

Characterization of Credit Ratings (Source: Moodys)		Ficth		Moodys		Linear Transformation
		Score Rating	(%) Index	Score Rating	(%) Index	Scale 11
Highest Quality	Investment Grade (IG)	AAA	0.1	Aaa	0.31	1
		AA+	0.63	Aa1	1.34	2
High Quality		AA	2.18	Aa2	2.26	3
		AA-	7.01	Aa3	6.97	4
		A+	11.27	A1	10.14	5
Strong payment capacity		A	14.76	A2	11.33	6
		A-	17.32	A3	15.42	7
		BBB+	15.38	Baa1	21.74	8
Adequate payment capacity		BBB	18.09	Baa2	18.37	9
		BBB-	7.11	Baa3	10.1	10
Ongoing uncertainty	HY	BB+	0.48	Ba1/Ba2	0.38	11
		NR/WD	5.66	NR/WD	1.63	N/A

Table 2.1: Moody's and Fitch rating systems and linear transformations

like coupon rate, seniority, and option features, hence making ratings a standard choice to measure credit-risk of a corporate bond.

Historical ratings are assigned at the bond-level. Investment grade is defined as BBB- or higher from Fitch Ratings and S&P Global Ratings and Baa3 or higher from Moody's Investor Service. Table 2.1 shows the distribution of the ratings according to each rater. The ratings are transformed in linear scale; for example, 1 refers to highest credit quality (AAA / Aaa), rating 2 follows (AA+/ Aa1), and so on. Investment-grade bonds have ratings from 1 (AAA, Aaa) to 10 (BBB-). Non-investment-grade bonds have ratings above 10. Therefore, a higher value indicates a better rating and higher credit risk. The average rating is calculated when both ratings are available. When only one rating is available, the rating provided becomes the rating value. Ratings are consolidated to the nearest previous rating grade, assuming that if there is no rating change, the credit quality remains unchanged. A.3 displays the breakdown distribution between the two credit ratings.

Illiquidity

Illiquid bonds refers to bonds that cannot be sold or exchanged without a substantial loss (for instance, trading volumes $<$ \$1 million/month). On average lower liquidity tends to go further away from the true mid-point of market prices(Bessembinder et al., 2008). Several studies focus on illiquidity proxies to account the role of liquidity in assets (De Jong and Driessen, 2012; Amihud, 2002; Roll, 1984; Bao, Pan, and Wang, 2011). They provide evidence that the corporate bond excess returns have a significant exposures to liquidity risk in both US and European markets. Bao, Pan, and Wang (2011) calculates illiquidity using the negative autocovariance in relative price changes[6].

$$ILLIQ = -Cov(\Delta p_t, \Delta p_{t+1})$$

Downside Risk

Downside risk is the potential decline in value if the market conditions change. The standard measure of downside risk is Value-at-Risk (VaR). To proxy downside risk, we use the 5% VaR over the past 12 months.

The Factors: DRF, CRF, LRF

On the basis of these three measures, we implement the factor construction of Downside, Liquidity, and Credit Risk Factors. Downside risk factor (DRF) is constructed by independently sorting corporate bonds into 2×3 portfolios based on the 5% Value-at-Risk (VaR) and credit rating. DRF is the equally-weighted average return difference between the highest VaR portfolio minus the lowest VaR portfolio within each rating portfolio. Liquidity risk factor (LRF) is constructed by independently sorting corporate bonds into 2×3 portfolios based on illiquidity (ILLIQ) and credit rating. Credit risk factor CRF is the average of the CRF obtained from forming DRF, and LRF, where: $CRF = 1/2(CRF_{VaR} + CRF_{ILLIQ})$.

The appendix A.1 presents additional statistics summaries, GICS sector breakdown, and performance overview.

2.0.2 Climate Measures

European Climate Change Awareness News Index

If climate risk represents a systematic risk factor that drives returns, then a factor asset pricing model will be able to uncover exposures to this climate risk factor. If climate exposure relates to ESG scores, at the idiosyncratic channel it will be able to uncover the relationship of ESG and spreads.

Key to this analysis is finding a proxy for systematic climate risk. Coverage of climate change news papers articles, might be suitable candidate for creating a climate risk factor. Regressing the return series of any financial asset on the return series of the climate risk factor while controlling for other exposures to bond factors allows us to estimate an asset's climate risk sensitivity. An asset with high (low) carbon sensitivity generally rises (drops) in value when the climate risk factor rises. Hence, it is highly exposed to climate risks, even if the issuer has high ESG scores (or even if the issuer do not report on ESG at all).

The Media and Climate Change Observatory (MeCCO)[7], monitors 120 sources (across newspapers, radio and TV medias) in 54 countries in seven different regions around the world. Data

6. Other definitions use transaction data in volumes (De Jong and Driessen, 2012; Amihud, 2002), but only specialized transaction datasets include this variable

7. More information may be found at: http://mecco.colorado.edu

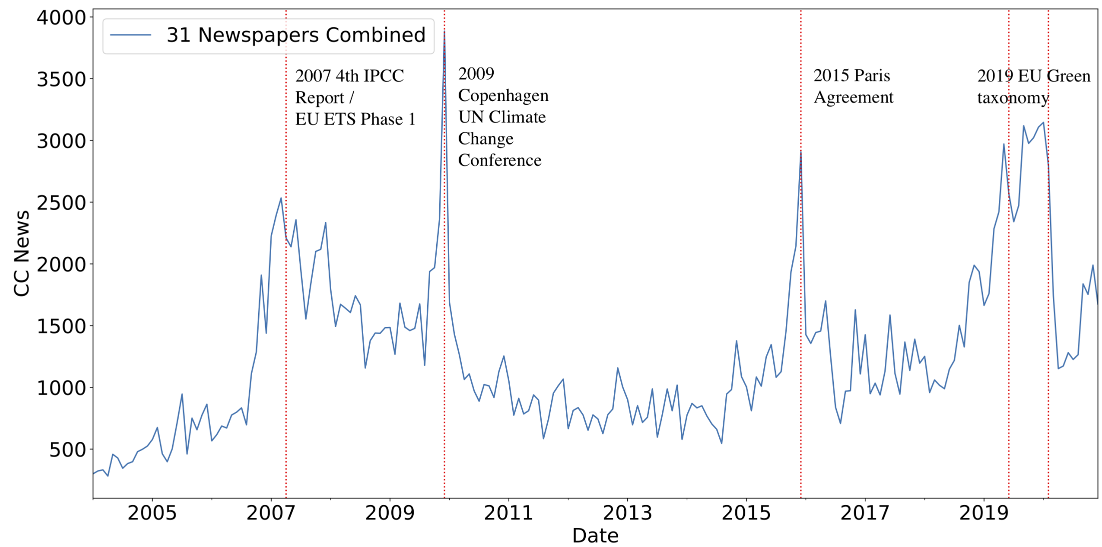

Figure 2.1: Newspapers coverage of climate change or global warming in Europe, from January 2004 through December 2020.

is assembled by accessing archives through the Lexis Nexis, Proquest and Factiva databases. The European database, published by Hawley et al. (2021), is composed of 31 european newspapers. From 2004 to December 2020, the database selects articles related to Climate Change or Global Warming. Figure 2.1 plots the coverage of the 31 newspapers combined. Table A.6 gives the list of newspapers.

The index spikes around major climate events, such as climate conferences (such as, the 2009 UN Climate Change Conference in Copenhagen), and related to climate regulations (the 2015 Paris Agreement and the 2019 EU taxonomy technical report by the TEG). At the beginning of the 2020, the number of climate news dropped significantly, the red line on the far right indicates January 24 2020, the first European case of COVID-19 reported in France. As the pandemic cases went up, the climate change received less attention.

Climate Change Beta

The Climate Change index is constructed to reflect the intensity of climate risks. Via newspapers articles, climate concerns can be measured. Climate change news beta (βCC_{news}) is constructed by calculating the percentage change from the previous month. For each bond i in each month t, rolling regression of bond excess returns are regressed on the monthly news change. The rolling β are estimated over a 3, 6, 12, and 18 monthly windows. $X_{i,t}$ represents a vector of bond-level control variables (i.e., downside risk, maturity, ratings, illiquidity, bond market beta, and spreads), and Y a vector of firm-level control variables (market capitalization, and ESG).

$$R_{i,t} = \alpha + \beta CC_{news,i,t}\gamma + \beta_X X_{i,t} + \beta_Y Y_{i,t} + \varepsilon_{i,t}$$

Further we add CC_{high} which is a dummy variable representing the period when the number of news is above the historical median (2015-2020). Then, we analyze the interaction between CC_{high} and βCC_{news}.

2.0.3 Exploratory Analysis

ESG, CO2, and Credit Ratings

Figures 2.2 and 2.3 plot CO2 emissions of Scope (1 + 2), and MSCI IVA scores over credit ratings, respectively. It is interesting to see in figure 2.2 that there are just a few outliers with high CO2 emissions. This goes along with the CDP Report showing that only just 100 companies are responsible for 71% of total global emissions. All of these, have ratings A or below. In figure 2.2, the average ESG score are quite similar across ratings. However, ESG scores have a wider variance over higher credit risks. While AAA companies ESG of 5 or above, BBB companies have between 0 and 10. These two plots show that AAA companies seems to be less exposed to ESG risks and CO2 exposure.

Univariate Portfolios

Table 2.2 shows excess returns of two univariate quintile portfolios sorted on credit ratings and ESG ratings. As opposed to credit ratings, that show a clear risk premium for higher credit risk portfolios. At first glance, for ESG there is no clear monotonicity of returns.

Bivariate Portfolios

Regarding bivariate sortings, Table 2.3 reports average monthly excess returns for the 5 × 5 portfolios independently sorted on Rating and VaR, Rating and ILLIQ, and Rating and ESG. For the 3 panels, returns increase with the level of riskiness for both variables. But again, high ESG risks doesn't follow an observable pattern. This resonates with the findings of Barth, Hübel, and Scholz (2019), where the risk mitigation effect has a U-shaped form across ESG quintiles.

2.0.4 Factor Model

Inspired by Fama and French (1993) and Bai, Bali, and Wen (2019), we construct the Climate 3 factor bond model. The factors DRF, CRF, LRF, and MKT are the factors betas. At the cross-section, we examine the relationship between the factors and returns, including the percentage change of Climate related news from the previous month[8]

$$R_{i,t} = \alpha_{i,t} + \Delta CCNews + \beta_{i,t}^{Factors} + \epsilon_{i,t}$$

Table 2.4 presents the estimates. We compare three different factor constructions. β_{EURO} are the factors as described previously. $\beta_{EURO\perp}$ are the orthogonalized factors. Because bond characteristics are highly correlated, downside, liquidity, and credit are intrinsically attached. To remove potential multicolinearity issues, we orthogonalize β_{EURO} by taking the residuals

8. Climate News are similar to risk factors, in the sense that all the constituents have exposure to the climate.

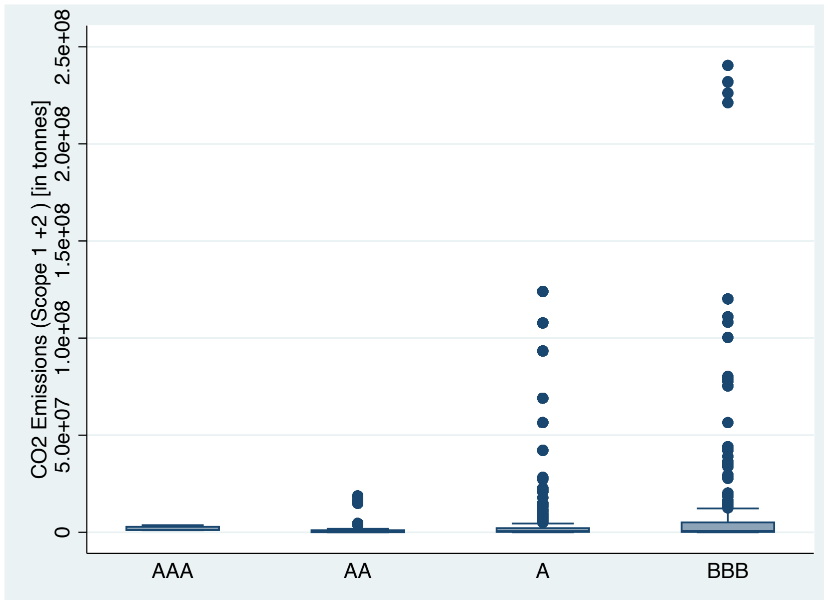

Figure 2.2: CO2 Emissions Scope (1+2) over Credit Ratings

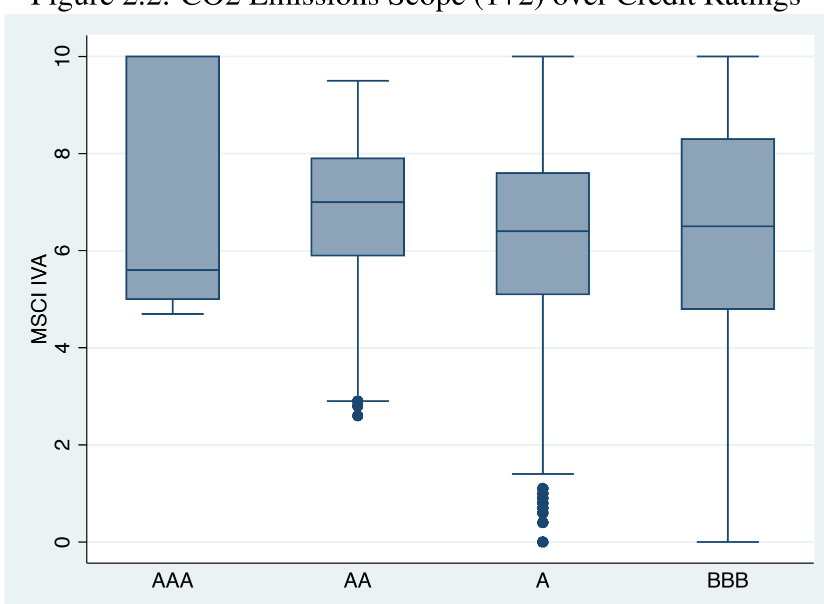

Figure 2.3: MSCI IVA Scores over Credit Ratings

Panel A: Univariate sort by credit rating			Panel B: Univariate sort by ESG rating		
	Rating	Average return		ESG Score	Average return
Low credit risk	4.16	0.17	Low ESG risk	8.31	0.22
2	6.36	0.20	2	7.66	0.18
3	7.86	0.22	3	6.48	0.18
4	8.78	0.25	4	5.22	0.20
High Credit risk	9.85	0.28	High ESG risk	2.92	0.27
High - Low	5.69	0.89	High - Low	5.39	-0.10

Table 2.2: Univariate portfolios of corporate bonds sorted by credit rating, and ESG score. Quintiles portfolios are formed every month from December 2015 to December 2020 by sorting corporate bonds based on their credit rating (Panel A), and ESG MSCI IVA score. (Panel B). The portfolios are equally-weighted. Ratings are linearized, where 1 refers to AAA rating, and so on. ESG score are in their conventional score (1-10). Higher ESG risk means lower rating, as opposed to credit ratings where higher scores indicate greater risk. Risk-free rate based on JP Morgan one-month EUR Cash Index.

from each factor[9]. β_{BAI} are the original (Bai, Bali, and Wen, 2019) factors[10]. All the variables are statistically significant. The results indicate that CRF is the main predictor of bond returns. Overall, bond factors can capture variation in bond returns, with a R^2 equal to 0.36. β_{BAI} have less magnitude because their construction is based on US bond market characteristics, and out-of-sample (from TRACE). Even so, there are signs of common variation across markets. The $\Delta EuroNews$ is negative and statistically significant of 0.048 indicates that an increase in the climate change European news is associated with a drop of 10 bps (=0.048×2.095) in the next month's bond excess returns.

We corroborate the relationship with World News. Even if the magnitude is smaller, the coefficients remain negative statistically significant. Thus, European Climate News are more closely related to EURO bond prices, than global Climate News.

Rolling β

Next, we estimate the climate sensitivity at the bond-level. Table 2.6 presents the results with monthly rolling windows 3, 6, 12, and 18 on βCC_{news} and control variables measured in month t. Excluding the 12-month rolling window, the coefficients are negative and statistically significant. This indicates that bonds with higher climate change news betas have lower future returns. Hereafter we will use the longer window ($18M\beta CC_{news}$), as this provides better accuracy of the estimates. Longer rolling window sizes tend to yield smoother rolling window estimates than shorter sizes. At the beginning, and the end of the period, we set the minimum

9. B describes in detail this procedure
10. The LRF, CRF, and DRF factors are available online at Jennie Bai's website

Panel A: Independently sorted 5 × 5 of Rating and VaR					
	Low VaR	2	3	4	High VaR
Low credit risk	0.18	0.20	0.19	0.17	0.12
2	0.21	0.23	0.22	0.19	0.16
3	0.24	0.26	0.24	0.22	0.17
4	0.23	0.23	0.20	0.18	0.18
High credit risk	0.28	0.31	0.28	0.26	0.23

Panel B: Independently sorted 5×5 of Rating and ILLIQ					
	Low ILLIQ	2	3	4	High ILLIQ
Low credit risk	0.18	0.15	0.15	0.18	0.24
2	0.21	0.17	0.19	0.20	0.27
3	0.22	0.21	0.21	0.21	0.28
4	0.23	0.21	0.20	0.22	0.26
High credit risk	0.27	0.25	0.24	0.24	0.32

Panel C: Independently sorted 5×5 of Rating and ESG					
	Low ESG risk	2	3	4	High ESG risk
Low credit risk	0.17	0.15	0.17	0.15	0.18
2	0.14	0.15	0.21	0.17	0.22
3	0.23	0.21	0.22	0.24	0.23
4	0.19	0.19	0.21	0.23	0.2
High credit risk	0.2	0.31	0.21	0.27	0.27

Table 2.3: Corporate bonds are sorted independently into 5×5 quintiles every month from December 2015 to December 2020 based on credit rating and 5% Value-at-Risk (VaR). The intersections of the two sorts produce 25 equally-weighted Rating-VaR portfolios in Panel A. Corporate bonds are sorted independently into 5×5 quintiles every month from February 2016 to December 2020 based on credit rating and illiquidity (ILLIQ). The intersections of the two sorts produce 25 equally-weighted Rating-ILLIQ portfolios in Panel B. Corporate bonds are sorted independently into 5×5 quintiles every month from December 2015 to December 2020 based on credit rating and ESG. The intersections of the two sorts produce 25 equally-weighted Rating-ESG portfolios in Panel C. The table reports averages of monthly excess returns of the 25 portfolios. Risk-free rate based on JP Morgan one-month EUR Cash Index.

	β_{EURO}	$\beta_{EURO\perp}$	β_{BAI}
$\Delta EuroNews$	-0.0487***	-0.0499***	-0.0261***
	(0.000253)	(0.000287)	(0.000232)
CRF	0.209***	0.263***	-0.000103***
	(0.00766)	(0.00858)	(0.0000199)
LRF	-0.00923***	-0.0487***	-0.00550***
	(0.000120)	(0.000386)	(0.000115)
DRF	-0.0431***	0.00397***	0.00358***
	(0.000296)	(0.0000942)	(0.0000536)
MKT	-0.433***	-0.474***	-0.299***
	(0.0135)	(0.0146)	(0.0137)
cons	0.00982***	0.0121***	0.0150***
	(0.0000793)	(0.0000940)	(0.0000799)
Adj.R-squared	0.365	0.356	0.183
N	10888	10888	10888

Table 2.4: This table reports the average intercept and slope coefficients from the Fama and MacBeth cross-sectional regressions of one-month-ahead cor-porate bond excess returns on the bond market betas. The bond market betas are β_{CRF}, β_{LRF}, β_{DRF}, and β_{MKT}. Δ EuroNews is the percentage change of news related to Climate Change or Global Warming from 31 European newspapers. β_{EURO} are the newly constructed factors. $\beta_{EURO\perp}$ are the orthogonalized factors. β_{BAI} are the US bond factors provided by (Bai, Bali, and Wen, 2019). Standard Errors are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Variables are defined in the main text of the paper

	β_{EURO}	$\beta_{EURO\perp}$	β_{BAI}
$\Delta WorldNews$	-0.0326***	-0.0271***	0.0176***
	(0.000742)	(0.000795)	(0.000632)
CRF	0.155***	0.207***	0.000605***
	(0.00253)	(0.00271)	(0.0000108)
LRF	-0.00883***	-0.0330***	-0.00108***
	(0.0000447)	(0.000333)	(0.0000676)
DRF	-0.0369***	-0.000948***	0.00166***
	(0.000172)	(0.0000999)	(0.0000243)
MKT	-0.111***	-0.136***	-0.152***
	(0.00610)	(0.00740)	(0.00913)
cons	0.0137***	0.0159***	0.0165***
	(0.0000441)	(0.0000415)	(0.0000564)
Adj.R-squared	0.232	0.202	0.093
N	48840	48840	48840

Table 2.5: This table reports the average intercept and slope coefficients from the Fama and MacBeth cross-sectional regressions of one-month-ahead corporate bond excess returns on the bond market betas. The bond market betas are β_{CRF}, β_{LRF}, β_{DRF}, and β_{MKT}. Δ WorldNews is the percentage change of news related to Climate Change or Global Warming from 120 global sources. Standard Errors are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Variables are defined in the main text of the paper.

	Dependent Variable: Excess Returns in t +1			
	(1)	(2)	(3)	(4)
$3M\beta CC_{news}$	-0.0637***			
	(0.00176)			
$6M\beta CC_{news}$		-0.139***		
		(0.00338)		
$12M\beta CC_{news}$			0.124	
			(0.1394)	
$18M\beta CC_{news}$				-0.0688***
				(0.0148)
_cons	3.594***	4.345***	5.424***	4.417***
	(0.244)	(0.244)	(0.261)	(0.255)
Adj.Adj.R-squared	0.125	0.105	0.087	0.082
N	72112	72130	72136	72182

Table 2.6: This table presents the results from the rolling regression of future excess bond returns in month 3,6, 12, and 18 monthly rolling windows on β_{CC}. Both bond and year fixed effects are included in all regressions. Standard errors are clustered at the issuer level in all regressions. Standard Errors are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Variables are defined in the main text of the paper

	Dependent Variable: Excess Returns in t+1	
	(1)	(2)
β_{CC}	-0.0381***	-0.0399***
	(0.00935)	(0.00863)
$HighCC$	-0.00317***	-0.00316***
	(0.000399)	(0.000290)
$HighCC$ X β_{CC}	-0.464***	-0.460***
	(0.0691)	(0.0520)
Firm	Y	N
Year	Y	Y
Month	Y	Y
Controls	Y	Y
Adj.R-squared	0.083	0.084
N	63044	63328

Table 2.7: This table presents the results from the panel regressions of one-month-ahead bond excess returns of the nonlinear effect of climate change news beta on future excess return on corporate bonds, conditional on high periods of climate change news index over the sample period from December 2015 to December 2020 (Huynh and Xia, 2020). The regression results with β_{CC} rolled over 12 months. Standard Errors computed using clustered standard error at the issuer level, and bond level are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Control variables are defined in the Appendix.

number of observations in the window required to have a value to 3.

High Climate News: Non linear effect

Huynh and Xia (2020) suggest that the effect of the climate change news beta on future bond returns changes over time and is more pronounced during times of high climate change news. Engle et al. (2020) discuss briefly these time-varying properties. CC_{high} is a dummy variable representing the month when the number of news is higher than the historical median (2015-2020). We analyze the interaction between CC_{high} and βCC_{news}. The interaction has significant estimates, in times when the climate news are above the median, bond prices are more sensitive to climate than in periods with no news.

	Dependent Variable: Excess Returns in t+1					
	Environmental Pillar		Carbon Footprint		Energy Efficiency	
	Q1 E (1)	Q5 E (2)	Q1 Concerns (3)	Q5 Concerns (4)	Q1 Opportunities (5)	Q5 Opportunities (6)
βCC_{news}	-0.0428	-0.117***	-0.0443	-0.0615***	-0.0474	-0.0308**
	(0.0255)	(0.0229)	(0.0260)	(0.0112)	(0.0254)	(0.0104)
DOWNSIDE	-0.000351**	-0.0000624	-0.000278**	-0.000258***	-0.000253*	-0.000316***
	(0.000123)	(0.000103)	(0.000104)	(0.0000543)	(0.000123)	(0.0000687)
ILLIQ	0.00183*	-0.000388	0.000766	0.00173***	0.00163*	0.00190***
	(0.000756)	(0.000824)	(0.000626)	(0.000476)	(0.000697)	(0.000547)
β_{Market}	-0.000382***	-0.000394***	-0.000366***	-0.000426***	-0.000510***	-0.000443***
	(0.0000640)	(0.0000573)	(0.0000345)	(0.0000237)	(0.0000516)	(0.0000303)
log(Credit)	-0.00949	-0.00150	-0.0000184	-0.00177	-0.00312	-0.00516*
	(0.00555)	(0.00441)	(0.00326)	(0.00150)	(0.00502)	(0.00212)
log(Maturity, months)	-0.00323	0.00110	-0.000515	-0.000923	-0.00286	-0.00339**
	(0.00258)	(0.00144)	(0.00115)	(0.000732)	(0.00146)	(0.00129)
log(MarketCap)	9.82e-16	-3.95e-15*	7.10e-15*	-1.33e-15	2.34e-15	-1.61e-15*
	(4.93e-15)	(1.58e-15)	(2.97e-15)	(7.99e-16)	(3.50e-15)	(6.64e-16)
Firm	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
Month	Y	Y	Y	Y	Y	Y
cons	-2.724*	-3.540***	-3.071***	-3.648***	-1.869**	-2.302***
	(1.072)	(0.635)	(0.552)	(0.341)	(0.704)	(0.603)
R-squared	0.069	0.054	0.065	0.077	0.072	0.086
N	2301	2141	2400	7713	1865	4358

Table 2.8: This table examines the effect of βCC_{news} on future bond returns in Environmental measures. Subsamples are split in the lowest and highest quintiles based on firms' environmental profiles huynh2020climate. Columns 1 and 2 report the results of the subsample analysis based on whether the firm's MSCI Environmental score is top or bottom. Columns 3 and 4 report the results of the subsample analysis based on Climate Concerns -Carbon Footprint Exposure (Q1-Q5). Columns 5 and 6 report the results of the subsample analysis based on Climate Opportunities -Energy Efficiency measure (Q1-Q5). Standard errors (SE) are clustered at the firm level in all regressions. SE are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Variables are defined in the Appendix.

Climate Concerns vs. Climate Opportunities

By exploring subsamples related to the environmental performance of the firms, we explore if these have higher climate change sensitivity or not. Table 2.8 estimates top and bottom quintiles on Environmental scores (Q1 E, and Q5 E), Carbon Footprint (Q1 Concerns, and Q5 Concerns), and Energy Efficiency (Q1 Opportunities, and Q5 Opportunities). Indeed, climate performance is priced by the market. However, the two legs are not priced equally. For the Environmental pillar, only the top quintile has a negative and significant effect. The market also prices the top quintile for environmental concerns and opportunities. But good environmental performance is not rewarded by the market, nor makes them less sensitive to climate risks.

Spread Regressions

To analyze the extent to which ESG scores influence spreads at the firm-level, we adopt the following model specifications (Barth, Hübel, and Scholz, 2019; Crifo, Diaye, and Oueghlissi, 2017; Slimane et al., 2019). We run a regression model of the panel data with fixed time effects using all bonds rated ESG over the period 2015-2020. Let $\log(OAS_{i,t})$ be the logarithm of the option-adjusted-spread bid for bond i at month t. $X_{i,t}$ is the vector of control variables (credit rating, sector and modified duration). I check the robustness of the environmental dimensions by switching criteria (IVA, Environmental pillar, CO2 emissions, and Energy Efficiency). These dimensions disentangle the effects of climate strengths or concerns with more granularity.

$$\begin{aligned}
\log(OAS_{i,t}) &= \alpha_t + \beta_{esg} ESG_{i,t} + \beta_X X_{i,t} + \eta_{i,t} + \nu_{i,t} + \epsilon_{i,t} \\
\log(OAS_{i,t}) &= \alpha_t + \beta_E Ei,t + \beta_X X_{i,t} + \eta_{i,t} + \nu_{i,t} + \epsilon_{i,t} \\
\log(OAS_{i,t}) &= \alpha_t + \beta_{Risks} Risksi,t + \beta_X X_{i,t} + \eta_{i,t} + \nu_{i,t} + \epsilon_{i,t} \\
\log(OAS_{i,t}) &= \alpha_t + \beta_{Opp} Oppi,t + \beta_X X_{i,t} + \eta_{i,t} + \nu_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{2.1}$$

Results show that ESG, and Environmental pillar minimize OAS. In general, the presence of unobserved factors are controlled with firm and time fixed effects. Consistent with Slimane et al. (2019), the regression yields high R^2, all above 56%. The beta coefficients of Credit Ratings and Modified Duration are robust across specifications. Higher credit risks increases the spreads. For climate concerns, the estimates show a positive relationship with spreads. And as it was expected, higher Carbon Emissions Score (= concerns) increases the spreads. As spreads increase, bond prices decrease. For climate opportunities, there is no significant relationship with spreads. These results go in hand with the previous quintile regressions. Moreover, individual regressions of ESG show a substantial mitigation effect of risks across bonds.

	Dependent Variable : log(OAS)			
	(1)	(2)	(3)	(4)
Credit Rating	0.123***	0.120***	0.122***	0.131***
	-0.0219	-0.0233	-0.023	-0.0226
Modified Duration	-0.231***	-0.258***	-0.270***	-0.365***
	-0.0373	-0.0405	-0.0414	-0.046
MSCI IVA	-0.0185**			
	-0.00565			
E		-0.0278**		
		-0.00956		
Carbon Emissions Score (Concerns)			0.0412*	
			-0.0186	
Energy Efficiency Score (Opportunities)				-0.0299
				-0.0159
cons	6.017***	6.121***	6.511***	7.438***
	-0.413	-0.445	-0.457	-0.437
Firm	Y	Y	Y	Y
Industry	Y	Y	Y	Y
Time	Y	Y	Y	Y
Adj.R-squared	0.638	0.639	0.64	0.625
N	41949	37400	37332	35235

Table 2.9: This table presents the results of spreads regressions (Slimane et al., 2019; Barth, Hübel, and Scholz, 2019). The dependent variables are the logarithm of Option-Adjusted-Spreads. The explanatory variables are credit ratings (linearized, beginning at AAA = 1), MSCI IVA ratings (ESG), Environmental pillar, Carbon Emissions (Concerns), Energy Efficiency (Opportunities) and a set of control variables. The sample period is from December 2015 to December 2020. All variables are explained in detail in Appendix A1. t-statistics are in parentheses. All model specifications include firm fixed effects and time fixed effects. Standard errors are clustered by firm and sector (Cluster firm industry) and by time (Cluster time).

Section 3

Conclusion

In resonance with Huynh and Xia (2020), we found a negative relationship with β_{CC} and prices. The decrease in demand for highly exposed bonds is expected to become more pronounced. Thus, investors are willing to accept lower expected returns from bonds less climate-sensitive bonds, for hedging purposes.

But only in times of high climate awareness. This means that in Europe fears about potential losses in consumption (transitional risks) increase only during times of heightened climate change news risk. This high climate awareness is concentrated close to worldwide climate events. After the event, the number of news goes back to lower levels.

No long ago, climate risks have started to be a major concern among investors. Thus, major attention to this risk will continue to increase. The plot A.5 shows the average β_{CC} across time. There has been a considerable increase during the last months. Indeed, indirect evidence for this suggestion comes from the fact that the demand for ESG measures has increased significantly recently.

Limitations

Different from bond-level credit ratings, ESG score ratings are constructed at the firm-level, as the calculation requires data from the output of each business model. Bonds issued by the same firm may have a similar probability of default but not necessarily have the same recovery rate, liquidity risk, market risk or downside risk. Because bonds issued by the same firm have different characteristics (duration, coupon, ttm), this implies different returns. Studies using aggregate variables must be interpreted with caution if bond-level measurements are not available. We are aware of this constraint since aggregated variables might produce spurious relationships with other variables in asset pricing models. This is known as aggregation bias. To overcome this bias, we have analyzed the bonds from the risk factor perspective and ESG at the portfolio-level (Q1-Q5).

[1]

1. For sovereign and municipal bonds, the level of aggregation is less restrictive since aggregated ESG scores are proxied at a regional-level or country-level. Even so, just a few papers have matched ESG data at the CUSIP

Selection Bias

In periods when the global scene focus on other issues, such as geopolitical or health issues, the focus on climate change decreases. Though, this doesn't mean that climate risks are less prone to occur.

Physical risks

Climate risks have started to materialize and it is difficult to fully hedge against the risk in the long run as climate change is worsening with time

Climate disasters are unexpected, and by definition impossible to predict. However, it is a fact that climate-related extremes are becoming more common, and without risk mitigation, could result in even greater losses in the coming years. Controlling, thus minimising economic losses and other harms, in case of unexpected events is key. Indirectly, one way to do it is by lowering the exposure to regulatory, and transition risks. The reduction of carbon footprint is best suited to be managed at the portfolio-level. But this translates into just adapting the portfolio weights. Another way is by reducing the sensibility to regulatory and transition risks, which in this case is the neutralization of β_{CC}.

Transition, and regulatory risks

New climate regulations creates winners and losers from regulatory risks. Since β_{CC} refers mostly to regulatory risks, less exposed bonds might increase the probabilities of success in the case of stricter regulations.

3.0.1 Final Remarks

In this study, we examine the effect of climate change news risk on individual corporate bond returns. We construct a climate change news beta, β_{CC}, that captures a bond's covariance with the climate change news risk index. We show that bonds with higher β_{CC} are associated with lower future returns and the effect of β_{CC} is more pronounced during periods of high climate awareness, which is situated near worldwide climate conferences.

These results are consistent with the hypothesis of intertemporal hedging demand, which posits that investors are willing to pay higher prices for (and accept lower future returns on) bonds with a higher β_{CC}, since these bonds offer better potential to hedge against climate change risk.

Further analysis of issuers' environmental profiles suggests that opportunities and concerns are priced differently. The study's findings also suggest that a firm's investment in improving its environmental performance will help lower its cost of debt financing, especially when the market is most concerned about climate change risk. These findings have important implications for business managers and regulators when attempting to emphasize the important roles of climate change risk, as well as socially responsible investments.

level on sovereign fixed income markets (Crifo, Diaye, and Oueghlissi, 2017; Capelle-Blancard et al., 2019).

Further Research

Finally, it would be interesting to extend the study of climate sensitivity index into a larger multi-asset framework. We leave this for potential future development. Following the advice of Lopez de Prado (2020), sustainability topics in fixed income can be enriched using Machine learning (ML) techniques needed to identify complex patterns and climate-related variables.

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Appendix A

Tables, Graphs and Summary Statistics

A.1 Summary Tables

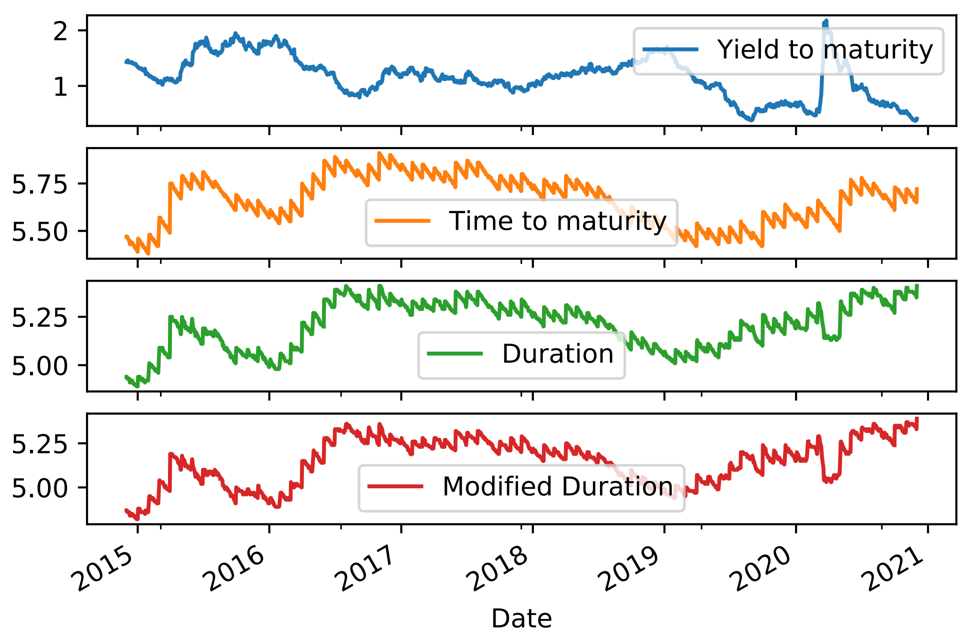

Figure A.1: YTM, TTM and (Modified) Duration

Study	Methods	Data	Universe	Period	Results
Devalle et al. (2014)	Multi Regression	KLD; Bloomberg; Mergent	56 Italian and Spanish firms	2006 - 2013	Lower cost of debt
Ge & Lui (2015)	Multi Regression	RiskMetrics, KLD, Mergent	4260 bonds from 2317 firms	1992 - 2009	Issue at lower cost
Menz (2010)	POLS FE and RE	Merrill Lynch index	498 bonds	2004 - 2007	Higher bond spread
Pavelin & Oikonomou (2017)	Multi Regression	KLD and Datastream	3240 bonds from 742 firms	1991 - 2008	Social posture impacts the cost of debt and the credit quality
Gianfrante et al. (2020)	Merton's DtD; Diff-in-Diff	Refinitiv' CO2; Bloomberg Barclays Agg Corp Index	458 firms	2007 - 2017	Negative relation of climate exposure and creditworthiness
Giese et al. (2020)	Exploratory Analysis	MSCI	MSCI FI index	2014 - 2017	ESG reduce risk
Ben Slimane et al. (2020)	Factor Approach	Proprietary ESG	ICE BofAML; EUR, USD and HY	2010 - 2019	Negative relation between ESG and Yields
Huynh & Xia (2020)	Factor Approach	Mergent; Engle (2020) CC News	8,231 bonds from TRACE	2002 - 2016	Environmental performance pay off when the market is concerned about climate change risk

Table A.1: Summary of Bibliographic References

	Last 1 year	Last 3 years	Last 5 years
Annualized Return (%)	1.30	3.18	2.66
Annualized Volatility (%)	6.01	5.15	5.46
Sharpe Ratio	0.22	0.62	0.49

Table A.2: Markit IBOXX EUR Corporates Index, FINE, as of 1 December 2020. Total Index return in excess of the risk-free rate, which is based on JP Morgan 1M EUR Cash index

2015-2020	mean	std	min	25%	50%	75%	max
Number of constituents	2338	432	1712	1961	2256	2660	3127
Modified Duration	5.18	0.12	4.89	5.08	5.20	5.27	5.40
Duration	5.23	0.11	4.98	5.14	5.26	5.32	5.42
Total Return Index	227.63	8.06	210.15	222.97	225.54	234.94	244.82
Time to maturity	5.67	0.12	5.42	5.57	5.69	5.77	5.91
Yield to maturity	1.09	0.36	0.31	0.84	1.11	1.31	2.18
2017-2020							
Number of constituents	2480	371	1937	2179	2410	2828	3121
Modified Duration	5.18	0.11	4.94	5.09	5.20	5.26	5.40
Duration	5.23	0.10	5.01	5.14	5.25	5.31	5.42
Total Return Index	230.09	6.90	219.60	224.93	226.91	237.74	244.82
Time to maturity	5.65	0.12	5.42	5.55	5.68	5.75	5.87
Yield to maturity	1.04	0.36	0.31	0.69	1.08	1.27	2.18
2020-							
Number of constituents	2996	104	2828	2882	3056	3101	3121
Modified Duration	5.26	0.10	5.03	5.20	5.29	5.33	5.40
Duration	5.30	0.08	5.13	5.25	5.33	5.37	5.42
Total Return Index	236.91	5.89	220.37	234.53	238.84	240.63	244.82
Time to maturity	5.66	0.07	5.50	5.60	5.67	5.71	5.78
Yield to maturity	0.84	0.45	0.31	0.53	0.68	0.99	2.18

Table A.3: Performance Overview

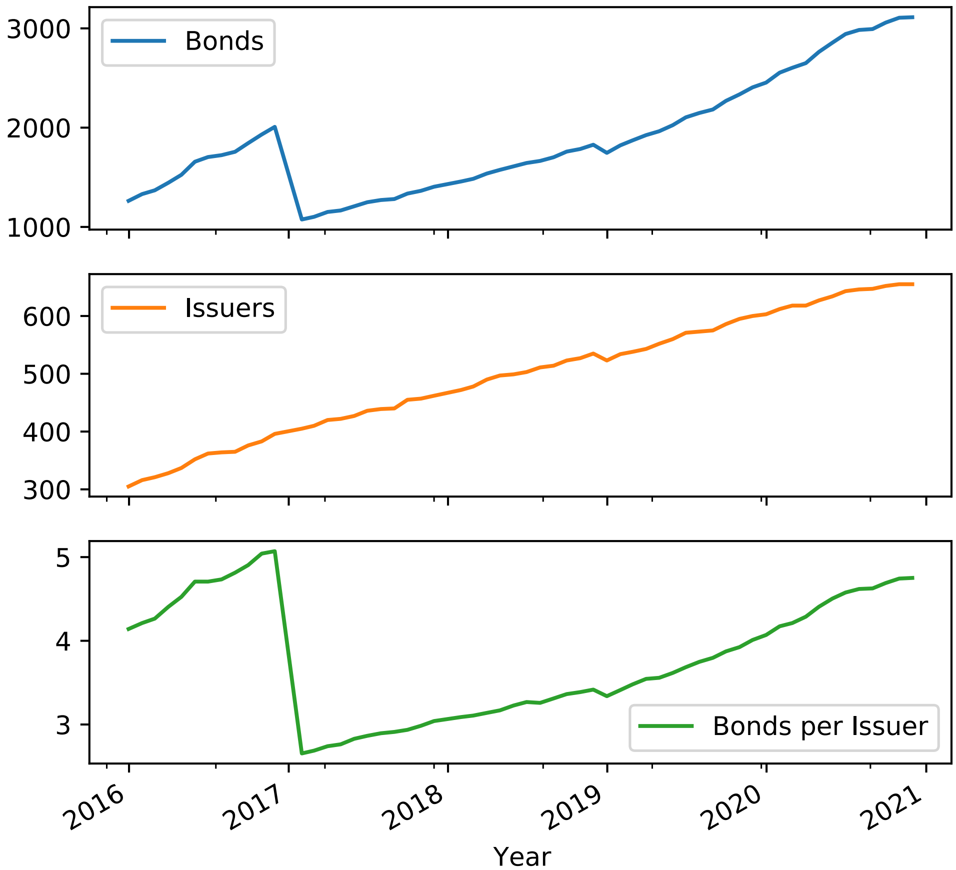

Figure A.2: Bonds, issuers, and bonds per issuer

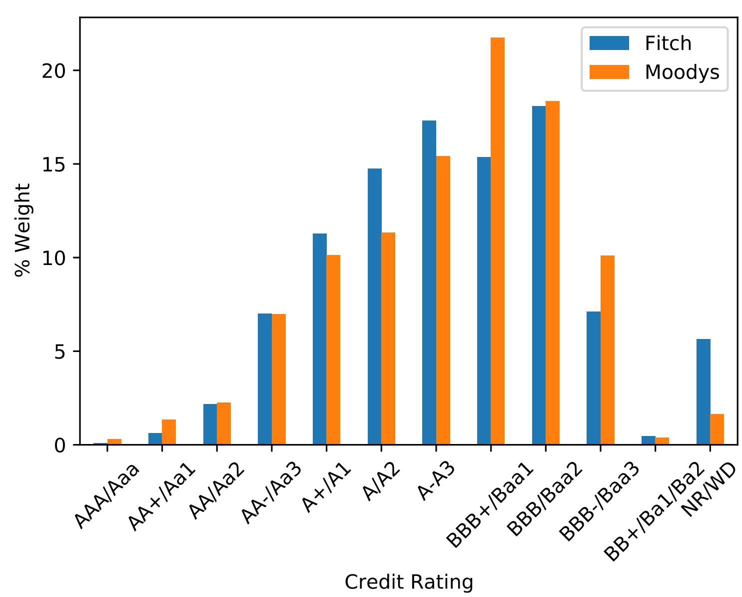

Figure A.3: Credit Rating Breakdown (Fitch/Moodys)

GICS Sector Name	(%) Index	Cumul. (%)
Communication Services	8.44	8.44
Consumer Discretionary	5.55	13.98
Consumer Staples	7.77	21.75
Energy	3.16	24.92
Financials	35.24	60.16
Health Care	6.66	66.81
Industrials	9.82	76.64
Information Technology	5.05	81.69
Materials	3.61	85.29
Real Estate	6.16	91.45
Utilities	8.55	100

Table A.4: GICS Sector Breakdown Source: Reuters, as of December 2020.

Using the Global Industry Classification Standard method (GICS) taxonomy, most companies are classified as Financials (35.24%), followed by Industrials (9.82%), Utilities (8.55%) Communication Services (8.44%) and Consumer Staples (7.77%). While in Europe the bond market is dominated by the financial intermediaries, the bond market in the United States is dominated by the non financial corporate sector. The finance literature in general excludes the financial sector (banks, insurance companies, among others), ADRs, REITs, and also as suggested by Fama and French (1993) *"units of beneficial interest are excluded"*. Therefore, the analysis with and without Financials and Real Estate companies is addressed.

A.1.1 European News Climate Change and Global Warming Time-series

CO2 emissions have a natural cyclical trend. Because of this bias, we cannot employ the percentage change. The data shows the need for adjustments with seasonal differences to address non-stationarity and seasonality. ACF suggest differencing the data with the 12 months lag.

Issuer Country Domicile	Freq.	Percent	Cum.
FR	553	19.70	19.70
NL	460	16.39	36.09
US	439	15.64	51.73
DE	254	9.05	60.78
GB	228	8.12	68.90
ES	133	4.74	73.64
LU	126	4.49	78.13
IT	97	3.46	81.59
SE	74	2.64	84.23
AU	67	2.39	86.62
BE	50	1.78	88.40
TOP-10	2481	88.4	
TOTAL	2807	100	

Table A.5: Top-10 Issuer country domicile

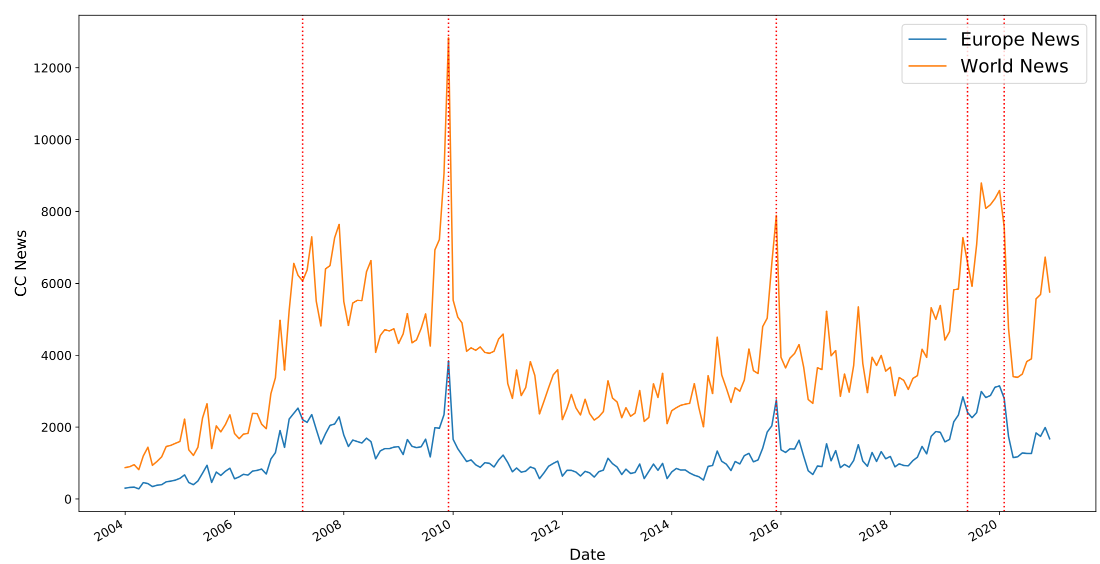

Figure A.4: Newspapers coverage of climate change or global warming Global, and Europe, from January 2004 through December 2020.

European Newspaper Coverage of Climate Change or Global Warming, 2004-2020 - December 2020				
			Average	
Newspaper	**Country**	**Total**	**Year**	**Month**
Jyllandsposten	Denmark	6462	538.5	44.9
Politiken	Denmark	8072	672.7	56.1
Berlingske Tidende	Denmark	5699	474.9	39.6
Daily Mail and Mail on Sunday	England	8290	518.1	43.2
Guardian and Observer	England	43357	3613.1	301.1
Telegraph and Telegraph on Sunday	England	16893	1407.8	117.3
The Daily Mirror and Sunday Mirror	England	7994	666.2	55.5
Times and The Sunday Times	England	33782	2815.2	234.6
Sun & Sunday Sun	England	8729	727.4	60.6
Le Monde	France	7588	632.3	52.7
Le Figaro	France	4997	416.4	34.7
Süddeutsche Zeitung	Germany	15789	1315.8	109.6
Die Tageszeitung	Germany	6923	576.9	48.1
Irish Times	Ireland	11579	964.9	80.4
La Repubblica	Italy	3217	268.1	22.3
Corriere della Sera	Italy	3320	276.7	23.1
Aftenposten	Norway	5376	448.0	37.3
Dagbladet	Norway	2793	232.8	19.4
VG	Norway	2762	230.2	19.2
Correio da Manhã	Portugal	1686	140.5	11.7
Izvestiya	Russia	642	53.5	4.5
Rossiskaya Gazeta	Russia	1554	129.5	10.8
Nezavisimaya Gazeta	Russia	1222	101.8	8.5
Komsomolskaya Pravda	Russia	472	39.3	3.3
El País	Spain	13006	1083.8	90.3
El Mundo	Spain	12819	1068.3	89.0
La Vanguardia	Spain	9100	758.3	63.2
Expansión	Spain	5293	441.1	36.8
Dagens Nyheter	Sweden	4575	381.3	31.8
Aftonbladet	Sweden	2207	183.9	15.3
Expressen	Sweden	2122	176.8	14.7
31 Combined Newspapers	Europe	258320	21526.7	1793.9

Table A.6: European Newspaper Coverage of Climate Change and Global Warming, 2004-2020

Date	Climate-Related Events
2007/09	4th IPCC Report / Record High Temperatures in Europe
2009/12	2009 Copenhagen UN Climate Change Conference
2015/12	Paris Agreement
2019/07	EU taxonomy technical report by the TEG
2020/02	COVID-19 Outbreak Europe

Table A.7: Climate-related European Events

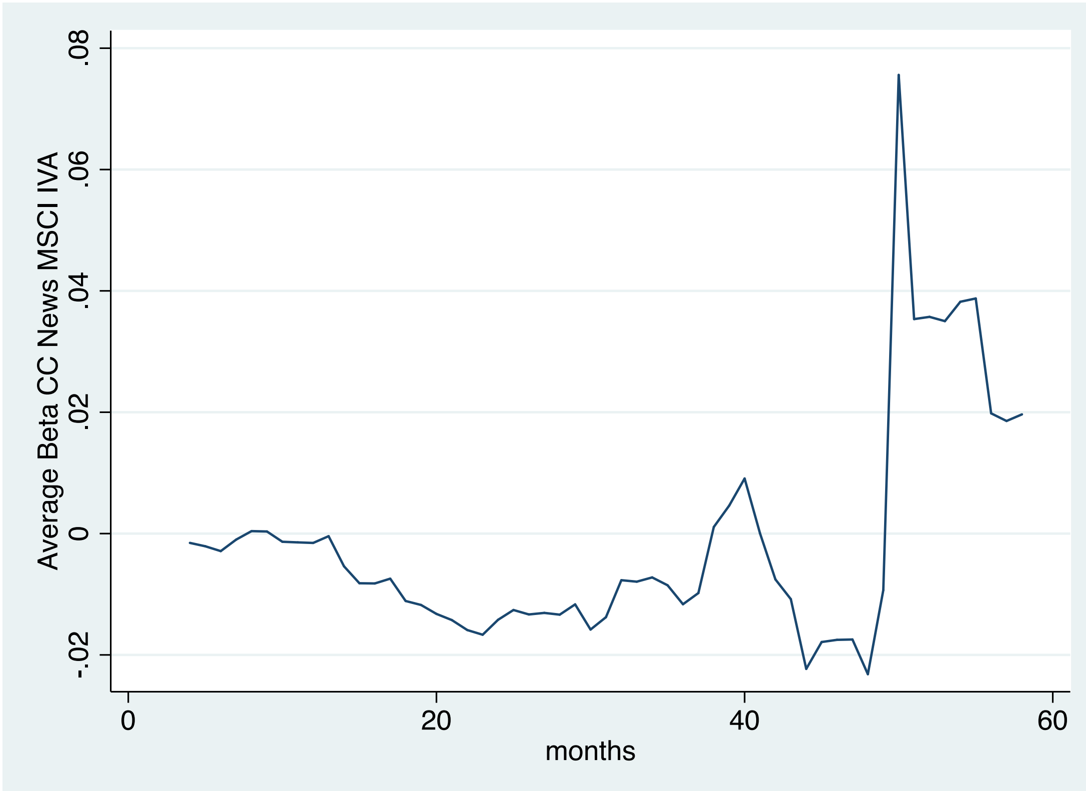

Figure A.5: Time-varying β_{CC}

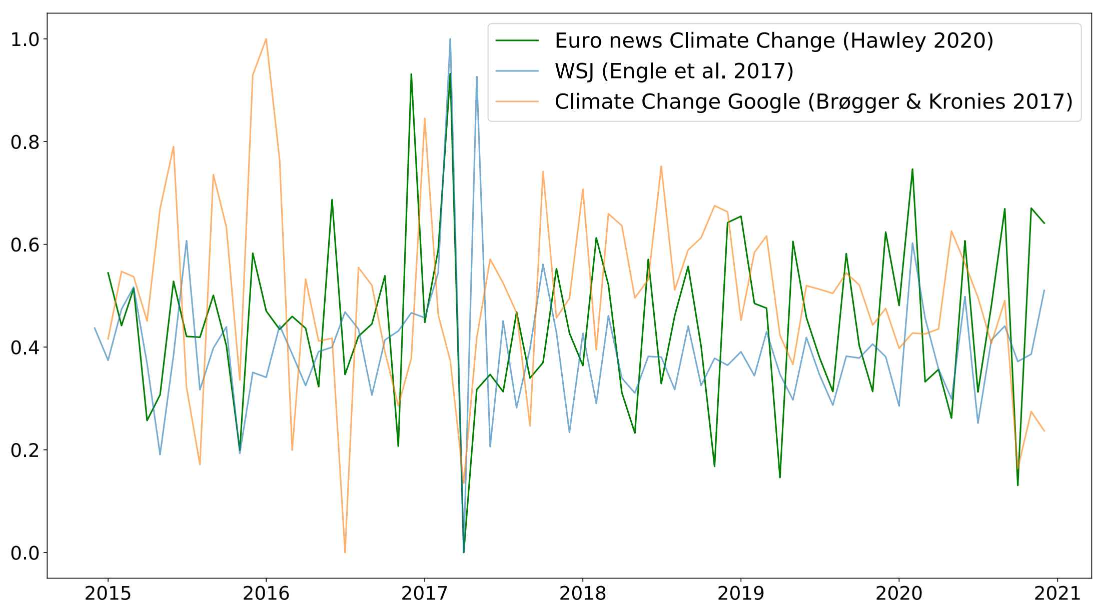

Figure A.6: Comparison of Climate metrics, in changes and standardized.

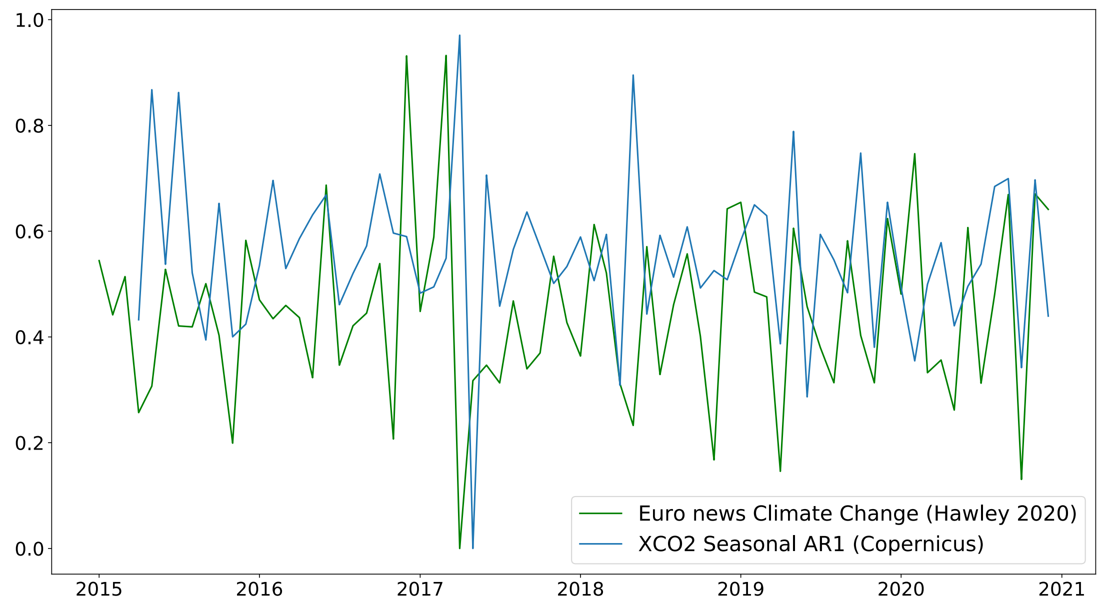

Figure A.7: Comparison of European climate change coverage and XCO2 emissions.

Variable	Definition	Source
$R_{i,t}$	A bond's monthly return in excess of the monthly risk-free rate, measured as a percentage. A bond's monthly return is calculated as in equation (1). The risk-free rate is proxied by the one-month JP Morgan 1M EUR Cash index.	Refinitiv
βCC_{news}	The climate change news beta is estimated from the monthly rolling regressions of individual bond excess returns on innovations in the monthly climate change news index over a 18-month window, after controlling for the excess market return, bond market illiquidity, downside, and credit. At least 3 monthly observations are required in the window to estimate beta.	MeCCo
ILLIQUIDITY	Bond illiquidity is computed at the end of each month t for each bond, using Bao illiquidity measure (Bao et al. (2011)).	Refinitiv
DOWNSIDE_RISK	The average of the four lowest monthly return observations over the past 36 months (beyond the 5% VaR threshold), multiplied by –1 and measured as a percentage (Bai et al. (2019)).	Refinitiv
log(MATURITY)	The natural logarithm of a bond's time to maturity, measured in years.	Refinitiv
RATING	A bond's credit rating as a numerical score, where 1 refers to an AAA rating.	Refinitiv
βCC_{MKT}	The bond market beta is estimated from the monthly rolling regressions of the excess bond market return. The excess bond market return is the monthly return on the Markit IBOXX Corporate Bond Index over the monthly JP Morgan 1M EUR Cash index.	FINE
ln(MARKET_CAP)	The natural logarithm of the market value of a firm's common equity (PRC × SHROUT) at the end of each month. The market value of equity is measured in thousands.	Refinitiv
ESCORE	MSCI ESG Industry-Adjusted Score	MSCI

Table A.8: Description of variables

Variable	Definition	Source
Final Industry-Adjusted Company Score	ESG Score to the Industry peer set, adjusted to reflect any Ratings Review Committee overrides; see the ESG Rating Methodology document for details.	MSCI
Weighted-Average Key Issue Score	The score represents the weighted average of the scores received on all the Key Issues contributing to the final rating of the company.	MSCI
Environmental Pillar Score	The Environmental Pillar Score represents the weighted average of all Key Issues that fall under the Environment Pillar.	MSCI
Carbon Emissions Exposure Score	Examples of criteria assessed include: the products and services a company provides; location of company operations; and the nature of those operations. Higher scores on exposure indicate greater risk on the Key Issue. (Score: 0-10)	MSCI
Energy Efficiency Exposure Score	Examples of criteria assessed include: the products and services a company provides; location of company operations; and the nature of those operations. Higher scores on exposure indicate greater risk on the Key Issue. (Score: 0-10)	MSCI
Product Carbon Footprint Exposure Score	Examples of criteria assessed include: the products and services a company provides; location of company operations; and the nature of those operations. Higher scores on exposure indicate greater risk on the Key Issue. (Score: 0-10)	MSCI
CO2 Equivalents Emission Total	Total CO2 and CO2 equivalents emissions. It is the sum of direct and indirect emissions. However, Scope 3 emission is excluded from total.	Refinitiv

Table A.9: ESG metrics

Appendix B

Mathematical Appendix

Portfolio-level Returns, and Factors

To calculate the systematic exposures of bonds portfolios described in the paper, portfolio's returns are noted $R(p, t)$. The regressions explain monthly excess price returns using the risk exposures (CRF, LRF, DRF) and the climate news percentage change. The model used is as follows:

$$R_{p,t} = \sum_{i=1}^{N} w_{i,t} F_{i,t}$$

This paper considers only equally-weighted portfolios, where w are the weights. The weight given for each issuer is $1/N$ and the weight for each bond m of issuer n by $1/N 1/M_n = w_{m,n}$. The sum of total weights is 1.

Israel, Palhares, and Richardson (2017) and Choi and Kim (2018) report that results don't change significantly for equally-weighted or value-weighted portfolios. Choi and Kim (2018) form two value-weighted portfolios, on asset and equity weights, these yield similar results. Furthermore, Baker and Wurgler (2012) and Bektić et al. (2019) use equally-weighted bond portfolios to avoid influence of large issuers. Accordingly, I employ this weighting scheme, arguing that all the issuers in this universe are exposed to environmental change, no matter the amount outstanding of debt issued or market capitalization.

Orthogonalized Factors

Bond risk characteristics are highly correlated. Bonds with higher downside risk also have lower credit quality and lower liquidity; bonds with higher market beta tend to have lower credit quality and higher downside risk. When putting them jointly in the regressions, mutli-colinearity problems arise. All these results lead to a concern about what unique information each risk characteristic carries. Following Bai, Bali, and Wen (2019), we construct orthogonalized risk characteristics, which are the residuals of each factor. For each month, we run contemporaneous cross-sectional regressions of one risk characteristic on the remaining three variables.

$$\begin{aligned} CRF_t &= \lambda_{0,t} + \lambda_{1,t}\beta_{i,t}^{MKT} + \lambda_{2,t}\beta_{i,t}^{LRF} + \lambda_{2,t}\beta_{i,t}^{DRF} + \varepsilon_{i,t}^{CRF} \\ DRF_t &= \lambda_{0,t} + \lambda_{1,t}\beta_{i,t}^{MKT} + \lambda_{2,t}\beta_{i,t}^{LRF} + \lambda_{2,t}\beta_{i,t}^{CRF} + \varepsilon_{i,t}^{DRF} \\ LRF_t &= \lambda_{0,t} + \lambda_{1,t}\beta_{i,t}^{MKT} + \lambda_{2,t}\beta_{i,t}^{CRF} + \lambda_{2,t}\beta_{i,t}^{DRF} + \varepsilon_{i,t}^{LRF} \end{aligned} \tag{B.1}$$