A study of the cross-section of climate bond returns[1]

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Abstract

In this study, I investigate common predictors in the cross-section of corporate bonds returns and evaluate to what extent these predictors apply to the returns of corporate bonds issued by climate-aligned firms, commonly referred to as climate bonds. I focus on the recently proposed bond-specific risk factors – downside risk, credit risk and liquidity risk – and use traditional bond-level and portfolio-level approaches to examine the differences between the general US corporate bond market and climate bonds. Our results differ from that of previous work on the subject, but overall the bond-specific risk factors perform well in explaining the returns of industry- and size/maturity sorted portfolios of corporate bonds for both traditional and climate-aligned firms.

Keywords: Corporate Bonds, Climate Bonds; Risk Factors

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1. Introduction

In recent years, there has been increasing focus on the role of the private sector regarding the necessary investments that need to be made for climate change adaptation and mitigation. Corporations, both financial and non-financial, have been identified by the global community as key actors in the efforts to reach both the United Nations' sustainable development goals and to limit global warming to a 2°C threshold by 2100 (UN, 2012, 2014; Climate Policy Initiative, 2015). With the intention of developing a European framework for sustainable finance, the European Commission has started to work on an action plan with clear objectives of reorienting capital flows towards sustainable investment and managing financial risks stemming from climate change (European Commission, 2018). The first measure taken by the commission is to develop a taxonomy to help actors of the private sector, as well as European Union member states, to differentiate economic activities based on their alignment with sustainability objectives. By developing a more transparent financial market where the corporations' different economic activities are well delineated, the commission wants to help financial actors understand as clearly as possible how their investments participate in different sustainability-related issues (TEG, 2020). This initiative was backed by regulation focusing on the notion of creating a more sustainable financial system (Council of the European Union, 2019) and is part of a general momentum that is already taking place for financial actors today. The Sustainable and Responsible Investing (SRI) industry has grown from \$23 trillion to \$30 trillion between 2016 and 2018 (GSIA, 2018), the green bond market reached the \$10 billion threshold in 2013 and represented more than \$257 billion in 2019 according to the Climate Bond Initiative (CBI)[4] and a nascent green loan market is developing, which represented close to \$100 billion in 2018 (Linklaters, 2019). Furthermore, what has been identified by the CBI as the "climate-aligned bonds universe" represented a total of \$1.45 trillion in 2018[5]. Though definitions of what constitutes sustainable investments and assets vary greatly between actors and geographical regions, and much work still needs to be done regarding the effective material investments that are made in sustainable projects, it is clear that business-as-usual is in the process of a major transformation to which financial and non-financial corporations will have to adapt, and financial markets with them.

In this regard, this paper constitutes an attempt to understand changes that might already be occurring on these financial markets due to the growing climate change urgency. Using transaction-based data spanning from June 2002 to March 2019, I analyze the cross-section of corporate bond returns of the US corporate bond market. By referring to a list of climate-aligned US firms provided by the Climate Bond Initiative, I obtain a dataset of climate bond returns spanning from June 2002 to March 2019. I then use these returns to determine the relationship between risk factors and the cross-

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[4]The Climate Bond Initiative is an international, investor-focused not-for-profit that focuses explosively on the bond market for climate change solutions. The amount of global green bond issuances is monitored on the organization's website. See https://www.climatebonds.net/.

[5] According to the CBI, this climate-aligned bond universe is composed of the \$389 billion labelled green bonds market, the \$314 billion market of corporate bonds issued by firms that originate more than 75% of their revenues from climate-aligned activities, the \$497 billion market of corporate bonds issued by firms that originate more than 95% of their revenues from climate-aligned activities, and the \$250 billion market of municipal bonds from issuers that originate more than 95% of their revenues from climate-aligned activities. See (CBI, 2018).

section of climate bond returns and understand the differences that might exist between corporate bonds issued by traditional firms and corporate bonds issued by climate-aligned firms.

One of the main research agenda in empirical asset pricing research focuses on studying the differences in expected returns across specific asset classes. To date, a large majority of this research has applied to stock returns given both the simplicity of these products compared to other market products and the availability of reliable data on stock prices. However, the global bond market represented a total of $102.8 trillion in securities outstanding in 2018, while the global equity market capitalization represented $74.7 trillion. In the US, these markets amounted to $41 trillion and $30 trillion respectively. Furthermore, the yearly value of US corporate issuances of debt products have been in average 9 times superior to the value of equity issuances between 2004 and 2018[6] (SIFMA, 2019). Given the size of these corporate debt markets, empirical asset pricing research on products that compose these markets could prove important for its different actors. However, corporate bond markets have historically been less accessible than stock markets for research. Quality data on bond markets had disappeared between 1997 and 2004[7] and corporate bonds are considered much more complex financial products given both the wide array of specific features these can have and the diverse risk exposures to both financial and macroeconomic factors they face. Fortunately, the Trade Reporting and Compliance Engine (TRACE) database and the Mergent Fixed Income Securities (FISD) database opened in 2002 and 2004 respectively, allowing authors to start working on the cross-section of corporate bond returns using bond-specific data.

Earlier research on the cross-section of corporate bond returns mostly developed factors using either stock-level data, treasury bond data and macroeconomic data. This is the case for the long-established Fama-French (1993) factors composed of the market risk factor (Mm-Rf), the size factor (SMB) and the book-to-market factor (HML) that originate from stock data and treasury bond data, and the term spread (TERM) and default spread (DEF) factors that originate from treasury bond data and government bond data[8]. Other factors that have complemented Fama and French's work, such as the liquidity (LIQ) factor (Pastor and Stambaugh, 2003), momentum (MOM) factor (Carhart, 1997), and more recently, the investment (CMA) and profitability (RMW) factors (Fama and French, 2015) all originate from stock-level data.

Realizing that these factors performed poorly in their ability to explain industry-sorted and size/maturity sorted portfolios of US corporate bonds, Bai, Bali and Wen (2019) introduced new bond-implied risk factors based on characteristics specific to corporate bonds. These characteristics were determined by focusing on the three most prominent differences between stocks and corporate bonds: (1) bondholders are more sensitive to downside risk given the fact that their opportunities in terms of upside are limited (2) bondholders are much more exposed to default risk and (3) as the corporate bond market is much more illiquid than stock markets, bondholders are more exposed to liquidity related risks. As a model composed of these factors and a market beta outperforms other models in the literature

[6] Corporate debt products include public and private, investment grade and high yield bonds, convertible debt, asset-back securities and non-agency mortgage-backed securities, while equity issuances include common stock issuances (IPOs and follow-ons) and preferred stock issuances.

[7] The Lehman Brothers Fixed Income Database closed in December 1997 and the Mergent Fixed Income Securities Database (FISD) opened in 2004

[8] In order to compute the default factor, a market portfolio of long-term corporate bonds was also required, and the data needed to compute such portfolio return could for the most part only be accessed through Ibbotson Associates, a private investment advisory firm.

to explain the cross-section of corporate returns for industry-sorted and size/maturity sorted portfolios, we use these factors as benchmarks to study differences between US climate bonds and the US corporate bond market. Following Bai, Bali and Wen (2019), we calculate bond returns using intraday transaction records from Enhanced TRACE data from June 2002 to March 2019. Much like the authors, our proxy for downside risk is the 5% value at risk (VaR) estimated from the second lowest monthly return observation in the past 36 months, our proxy for credit risk is the bond-level credit rating, and our proxy for liquidity is that developed in Bao, Pan and Wang (2011). We also develop a market beta measure in accordance with the literature.

Though we initially strictly follow the mythology of Bai, Bali and Wen (2019), our results vary. Across the entire dataset, we obtain lower bond returns, as well as lower downside risk. However, we obtain slightly higher illiquidity and lower market beta. Looking more specifically at US climate bonds, we observe even lower returns, much less variation in terms of credit ratings, much higher time to maturity, greater size, lower downside risk and average illiquidity, and similar market beta.

Our univariate and bivariate portfolio analysis still however illustrates a strong relationship between downside risk and next-month excess-bond returns. Regarding the general US market, bonds in the highest downside risk quintiles generate 3.12% higher yearly returns than bonds in the lowest downside risk quintiles. In the case of climate bonds, the yearly difference is of 2.28%. After controlling for the ten previously cited stock and bond factors, the risk-adjusted return difference between bonds in the highest and lowest downside risk quintiles is economically and statistically significant for the entire market with 2.76% return difference and a t-statistic of 4.40. Economic and statistical significance levels are just slightly inferior for climate bonds, with a yearly return difference of 1.92% and a t-statistic of 1.86.

Similarly, we study average portfolio characteristics and find that at the scale of the entire market, there seems to be a positive relationship[9] between downside risk and market risk, illiquidity, credit rating and maturity, while no such relationship seems to exist between downside risk and size, although in average bonds in the lowest downside risk quintiles are smaller than bonds in the highest downside risk quintiles. Similar relationships seem to exist for the climate bond sample as well, at the exception of credit rating which stays quite constant throughout the different levels of downside risk.

Given this information, we therefore also perform bivariate portfolio analysis and, continuing to follow the approach of Bai, Bali and Wen (2019), test if the relationship between downside risk and next-month bond excess returns is maintained when controlling for these characteristics. Our results are also both economically and statistically significant, with yearly differences in returns for the entire market of 2.28% after controlling for credit rating, 1.8% after controlling for maturity, 2.16% after controlling for size, and 1.8% after controlling for liquidity. Our results for climate bonds are also both statistically and economically significant, although to a slightly lower degree, with lower statistical significance for credit rating-, maturity- and liquidity-controlled portfolios, and lower economic significance for credit rating- and maturity-controlled portfolios.

I then perform bond-level Fama-Macbeth regressions in order to study the cross-sectional relationship between the three bond-specific factors, the bond market beta and next-month excess bond returns more specifically. Following the original methodology of Fama-Macbeth (1973) and continuing

[9] In the sense that as quintile portfolios represent bonds with higher downside risk, these portfolios constantly contain higher levels of each of the corresponding characteristics

to follow the specific approach of Bai, Bali and Wen (2019), I perform regressions of one-month ahead excess returns on downside risk, credit risk, liquidity risk and bond market beta, while controlling for bond exposures to default and term factors, maturity, size and lagged return. While our results regarding the statistically significant positive relationships between these factors and expected returns, as well as the statistically significant negative relationship between return reversal and expected return are quite similar to that of Bai, Bali and Wen (2019), we do find important differences, as we obtain some very statistically significant alphas as well as some statistically significant control variables.

We also compute factors following the methodology in Fama and French (2015) by relying on independent sorts. Once again, our results differ from results in Bai, Bali and Wen (2019), since our downside risk factor is neither – considering the time series averages - our largest factor not is it larger than the bond market risk premium of 0.58. Considering ten-factors alphas for the bond factors, the highest alpha is that of the return reversal factor (REV), which is more than twice that of our downside risk factor. Even though all our results are statistically significant, they do vary from Bai, Bali and Wen's previous work.

In order to verify our bond factors, we test these factors on industry- and size/maturity-sorted portfolios. Though our results also outperform previous models if we refer to adjusted R squared as measure for model performance, our results differ. Regarding tests on size/maturity portfolios, we obtain an average adjusted R squared of 0.49, but our results seem to greatly improve as maturity increases for portfolios. We obtain an average alpha of 0.15 across portfolios, with a great majority of alphas being statistically significant with an average t-statistic of 3.99. Looking at industry portfolios, our average adjusted R squared are of 0.50 across industries, with a slightly lower average alpha of 0.10 and a much lower average t-statistic of 1.86. Results are quite similar for climate bonds, which average a 0.46 adjusted R-squared for both size/maturity portfolios and industry-sorted portfolios.

2. Literature Review

Literature on the general subject of the relationship between finance and environment-related issues is still nascent. To date, two main subjects have been studied: the relationship between corporate environmental, social and governance (ESG) performances and corporate financial performance and the pricing of green bonds and the existence of a green bond premium.

A majority of studies and meta-analyses that focus on the relationship between ESG factors and corporate financial performance (CFP) reveal a positive association exists, even though work still needs to be done on establishing clearer causality (Schiereck, Friede and Bassen, 2019). This subject draws a lot of attention given the fact that it is at the cross-roads of different deeply rooted theories in literature. On the one hand, a positive relationship between ESG factors and financial performance is supported in the management literature by stakeholder theory (Donaldson and Preston, 1995), the resourced-based theory of the firm (Barney, Ketchen, and Wright, 2011) as well as in the literature that focuses on competitive advantage more specifically (Porter and Kramer, 2006). On the other, a negative relationship corresponds to more traditional financial and economic theories, such as Milton Friedman's view of the firm (Friedman, 1970) and his claim that the only social responsibility of the company is to increase its profits, and portfolio theory (Markowitz, 1959) which would consider the exclusion of certain stocks from portfolios for ESG-related matters suboptimal. Finally, we can consider that supporters of the efficient market hypothesis consider that all information – and therefore information included in ESG factors – are constantly considered by market actors (Fama,1991), and therefore that no specific relationship exists.

As a globally positive relationship seems to be established between ESG and financial performance, it is yet unclear what are the precise relationships between the different dimensions of ESG and corporate financial performance. Two important meta-analyses have emerged in the literature that have focused on gathering a wide range of studies in order to have a more precise understanding of the different possible ESG and CFP relationships (Busch and Friede, 2018; Friede, Busch, and Bassen, 2015). Friede, Busch and Bassen (2015) find that approximately 90% of studies find non-negative ESG-CFP relations, with 47.9% in vote-count studies and 62.6% of meta-analyses resulting in positive findings, while only 6.9% and 8.0% find negative relationships. These results hold across asset-classes, geographical regions and environmental, social and governance categories, and this positive relationship is even more pronounced in North America and Emerging markets, and for non-equity products. In their paper, Busch and Friede (2018) focus on the relationship between corporate social/environmental performance (CSP) and corporate financial performance (CFP) through a second-order meta-analysis and find a “highly significant, positive, robust, and bilateral CSP-CFP relation” and conclude that “based on the extant literature, the business case for being a good firm in undeniable.”

A branch of this literature focuses specifically on the relationship between environmental performance and financial performance of corporations. However, the definition of what constitutes corporate environmental performance (CEP) varies amongst authors. Authors still do not agree on whether environmental performance is a one-dimensional concept or a multi-dimensional one. Some authors directly construct one CEP measure while others differentiate between process-based environmental performance (Environmental Management Performance – EMP) and outcomes based environmental performance (Environmental Operational Performance – EOP). Furthermore, databases, metrics and samples vary. Using the ASSET4 ESG database Xue, Zhang and Li (2019) create a measure for EMP using 41 KPIs and measure EOP using Total CO2 and CO2 equivalents emissions in tonnes divided by net sales on a sample of UK firms while Trumpp, Endrikat, Zopf and Guenther (2015) use 32 KPIs for EMP and 5 continuous KPIs for EOP focusing on energy consumption, CO2, water withdrawal and produced waste on a sample of European and US firms. Using the same source of data, Escrig- Olmedo, Muñoz-Torres, Fernández-Izquierdo, & Rivera-Lirio (2017) use 61 KPIs to create one measure for CEP for firms in the agri-food industry and Hartmann & Vachon (2018) focus only on carbon emission reduction for EU manufacturing firms. This variety in terms of approaches and samples applies to other sources of data, such as for users of the KLD database (Ren, He, Zhang, & Chen, 2019; Post, Rahman, and McQuillen, 2015; Delmas, Etzion, and Nairn-Birch,2013), the CDP database (Misani & Pogutz, 2015; Trumpp & Guenther, 2017) or data originating from surveys (Xie & Hayase, 2007; Anton, Deltas, and Khanna, 2004; Bhattacharyya & Cummings, 2015). In addition to the challenge faced by the literature regarding this diversity of possible approaches, another challenge resides in the quality and comparability of environmental data that is provided by ESG databases (Kotsantonis and Serafaim, 2019).

As the evidence for a strictly positive relationship between corporate environmental, social and governance performance and corporate financial performance is being gathered in the literature, initiatives have emerged on the pricing of assets with underlying extra-financial purposes. Specifically, the growing number of issuances of green bonds since 2013[10] has led academics to develop an interest in this product. Green bonds are bonds issued in order to specifically finance projects with positive environmental outcomes, and naturally a stem of literature is focused on trying to determine if green bond issuers benefit from a green bond premium given the nature of their project.

However, this initiative has met important challenges. First and foremost, the pricing of bond products is more challenging than that of equity products, given the fact that bonds have multiple specific characteristics that directly impact their pricing, such as coupon rates, credit rating, maturity or size (Zerbib, 2019). Determining if a green bond premium exists would require comparing green bonds with traditional bonds that have precisely the same characteristics, which very rarely exist (Bachelet et al, 2019). In addition to these important limitations, the green bond market represented less than 3.6% of the global bond market issuances[11] in 2019, and issuances are still sporadic throughout the year, which leads both to issues in terms of liquidity, as well as in terms of available data for pricing. Moreover, the academic literature that focuses on studying the corporate bond market refers to one specific transaction-based database to obtain the best quality data on the pricing of corporate bonds – the TRACE database[12] – which only applies to US corporate bonds. For the year 2018, Moody's Analytics[13] reported that $1.553 trillion in bonds were issued in the US, while the Climate Bond Initiative reported $34 billion in US green bond emissions (Climate Bond Initiative, 2018). This represents less than 2.2% of US corporate bond emissions, meaning that academics that wish to study this database would have access to too little data to perform robust analyses.

Studies on the pricing of green bonds therefore generally have small samples and must refer to other databases with less precise pricing data, such as dealer quotes provided by market-makers or matrix-prices, which only provide approximations of real prices. To provide an idea of the general ranking of data on corporate bond pricing in terms of quality, Jostova, Nikolova, Philipov and Stahel (2011) built a database of bond returns using the five databases that gave information on corporate pricing and took "the first available return in the following sequence: TRACE, FISD[14], Lehman, Datastream and Bloomberg", clearly giving precedence to trade-based data. Combined, these restrictions in terms of sample size, historical data and pricing data quality results in inconclusive findings concerning the existence of a green bond premium (Hachenberg and Schiereck, 2018; Bachelet et al, 2019; Kapraun and Sheins, 2019, Zerbib, 2019). Similar studies have also focused on the relationship between ESG ratings and corporate bond performance, finding that bonds issued by firms with higher ESG ratings have tighter spreads and outperform peers with lower ESG ratings (Polbennikov, Desclée, Dynkin and Maitra, 2016). Ge and Liu (2015) find that better CSR performance is associated with better credit ratings. In a paper focusing specifically on corporate green bonds,

[10] With the first issuance of a green bond product dating to 2007, the green bond market reached the $10 billion milestone in 2013 and the $100 billion milestone in 2017. In 2019, the market represented $257.4 billion in global issuances.
[11] Global bond issuances in 2019 amounted to $7.148 trillion. See https://www.dealogic.com/insight/dcm-highlights-full-year-2019/
[12] As TRACE transaction data is the main source of data for this paper, more information is provided in section 4 of this paper on the specificities of this database
[13] See https://www.moodysanalytics.com/-/media/article/2019/weekly-market-outlook-corporate-bond-issuance-reflects-business-activitys-heightened-to-rates.pdf
[14] When referring to FISD, the authors referred to the NAIC databases which complements the FISD database, which itself only provides information on characteristic data of US bonds. The NAIC database provides transaction data on corporate bonds issued and traded by US insurance companies.

Flammer (2020) finds a positive reaction from stock markets to green bond issuance announcements, that green bond issuers improve their environmental performance after the issuance, and that they experience increase in ownership by long-term and green investors.

While most of the aforementioned literature focuses either on corporations' ESG performance and ratings or the performance of green bonds more specifically, this study focuses on traditional corporate bonds issued by corporations with climate-aligned activities. This approach, which consists in identifying climate-aligned business activities and differentiating them from non-climate-aligned business activities, though initially developed by the Climate Bond Initiative in order to identify and analyze a market of "climate-aligned bonds" or "climate bonds", is being integrated by the European Commission in an effort to help investors better identify sustainable firms and corresponding financial products. It is the author's belief that the European Commission is taking the lead in implementing a major shift in how corporations are viewed by investors though its EU classification system for sustainable activities. In that sense, this paper investigates if significant differences already exist between "traditional" firms and "climate-aligned" firms. As previous work by the Climate Bond Initiative has identified climate-aligned bonds starting from January 1st 2005, and that there are 55 US climate-aligned firms, the dataset of US climate-aligned bonds is sufficient to obtain economically and statistically significant results both through cross-sectional analysis and time-series analysis. To the author's knowledge, this study is the first to examine the cross-sectional determinants of climate bonds returns.

3. Data

3.1. Required databases for corporate bond and climate bond pricing

For this paper, we use three distinct sources of data. We obtain transaction data for the US corporate bond market through the TRACE database, which we use to compute corporate bond returns. We use the FISD database to obtain information on bond characteristics. Finally, we obtain a list of climate bond issuers from the Climate Bond Initiative, which we use to identify climate bonds through the FISD database.

Since June 2002, all corporate bond transactions in the secondary market have been made available with the TRACE system through the Trade Reporting Compliance Engine[15]. Before this new dataset was made available, most studies that focused on the corporate bond market only used daily quotes and matrix prices for corporate bonds, which could bias results. In their paper on the subject, Sarig and Warga (1989) explore the fact that there can be liquidity-driven noise errors in daily prices for corporate bonds since daily prices are given even on days when bonds have not been traded for multiple days. When this is the case, brokers set matrix prices based on similar bonds issued by issuers with similar characteristics, which creates bias. More recently, Dick-Nielsen (2009) shows that this bias still exists with prices from Datastream[16]. This gives TRACE data a considerable edge when focusing on daily

[15] The Trade Reporting and Compliance Engine (TRACE) was developed by the National Association of Securities Dealers (NASD) and is used for over-the-counter (OTC) transactions for fixed-income securities. This trade-based data is made available to academics through the TRACE database.

[16] As it is explained in Jostova, Nikolova, Philipov, Stahel (2013): "Extensive discussions with the DataStream support team about the source of their data confirmed that most U.S. corporate bond prices are dealer quotes reported by market-makers. These data are further augmented with trading prices for traded bonds. Like Lehman, DataStream provides no indication of whether a price is based on a quote or a trade."

prices that can be used for microstructure research such as event studies, as well as an edge for weekly and monthly prices.

Two distinct versions of TRACE exist: the standard TRACE data that censors trading volumes that are greater than $5 million for investment grade bonds and greater than $1 million for speculative grade bonds and that usually has a three-month lag for the availability of data, and the enhanced TRACE data, that has information on all transaction volumes but has an 18 month lag for the availability of data. In this paper, we refer to enhanced TRACE data, which spans from June 2002 to March 31st 2019.

Considering bond characteristic, FISD is considered as the most comprehensive database focusing on bonds and contains detailed information on the characteristics of more than 140,000 US bonds, either corporate bonds, supranational bonds, U.S. Agency Bonds and U.S. Treasury Bonds. The FISD database contains essential information on bond issuers as well as specific bond issues such as bond issue date, maturity, size, coupon, type, and any information that can be used to identify and categorize US bonds.

Finally, we use a list of climate bond issuers provided directly by the Climate Bond Initiative (CBI) research team. This list was used by CBI in their study on the climate bond market (Climate Bond Initiative, 2018). To identify climate bonds, CBI identified issuers that originated at least 75% of their revenues from green business lines in either clean energy, low-carbon buildings and transport, water and waste management and sustainable land use. Climate bonds were included if they were issued after the 1st of January 2005 and before the end of Q2 2018. Therefore, we use the list of issuers provided by the Climate Bond Initiative to identify all climate bond transactions available on the Enhanced TRACE database since June 2002 to the 31st of March 2019. Our database for traditional bonds uses all available Enhanced TRACE data on the same period.

3.2. From raw intraday transaction data to monthly corporate bond returns

As I continue to follow Bai, Bali and Wen (2019), I remove bonds that are not traded in in the US public market, bonds that are structured notes, mortgage or asset-backed, agency backed or equity-linked, convertible bonds, bonds with floating coupon rates, bonds that trade below $5 or above $1000 as well as bonds that have less than one year to maturity. Regarding transaction data, much like Bai, Bali and Wen, I remove bond transactions that are labeled as “when issued”, “locked-in”, that have special sales conditions and that have more than a two-day settlement. Furthermore, I also remove transactions that have a volume inferior to $10,000. Finally, I follow the filtering methodology developed in Dick-Nielsen (2014) to remove cancellations and corrections made on the TRACE Enhanced database, as well as inter-dealer transactions that are reported twice in the trace database. Much like the author, I apply the two distinct approaches for pre- and post-2012 Enhanced TRACE data. After applying these different filters, my dataset is composed of 91,294,517 intraday transactions spanning from June 2002 to March 2019.

Once we obtain this intra-day information on bond transactions, we compute a daily price by referring to the “trade-weighted price, all trades” approach of Bessembinder et al. (2009), which consists in performing a value-weighted average of all intraday transaction prices. This methodology puts more emphasis on trades from institutional investors that benefit from lower execution costs, therefore providing a better accuracy for daily prices. Once we apply this methodology, our daily price dataset consists of 13,770,971 daily prices[17].

In order to obtain monthly prices from daily prices, I develop a methodology similar to that of Bai, Bali and Wen (2019). I first identify the bond price for the last trading day for each bond-month. If the last trading day is one of the last five trading days within month *t*, then this daily price is used as a monthly price. If that is not the case, I identify the bond price for the first trading day of month *t+1*. If this trading day is one of the first five trading days of month t+1, it is used as a price for month *t*. This allows for a more complete dataset of bond monthly prices in order to be able to compute more monthly returns using data from months *t* and *t+1*, where returns are either computed using (1) end of month *t-1* to end of month *t* daily prices (2) start of month *t* to end of month *t* daily prices (3) start of month *t* to start of month *t+1*. Using the methodology, we compute 1,761,543 monthly prices for our dataset.

The monthly corporate bond return at time t is computed as:

$$r_{i,t} = \frac{(P_{i,t} + AI_{i,t} + Coupon_{i,t}) - (P_{i,t-1} + AI_{i,t-1})}{P_{i,t-1} + AI_{i,t-1}}$$

where $P_{i,t}$ is the transaction price, $AI_{i,t}$ is accrued interest, and $Coupon_{i,t}$ is the coupon payment, if there is any, of bond i for month t. We obtain the necessary information to compute corporate bond returns from the FISD database.[18] In order to compute our returns, month prices need to be available for adjacent months. Our final dataset is composed of 1,530,745 corporate bond returns.

4. Variable Selection

In the context of this study, we apply three bond-level factors developed by Bai, Bali and Wen (2019). Through their research, the authors observed that the literature that focus on the cross-section of corporate bond returns relied on stock market factors, based on the rational that the stock and bond markets are integrated, since both bonds and stocks value similar underlying assets. Their work goes against this more traditional approach by focusing on risk factors that are specific to the bond market.

4.1. Downside risk

One of the main concerns for bond holders regards extraordinary events that can lead to crashes on either the stock or bond markets. Both private companies and public regulators focus on understanding what are the minimal capital requirements in order to face such risks if they were to occur. Various methodologies have been developed by actors of the bond markets in order to measure such risks. Both practitioners and academics have recently focus on the concept of Value at Risk (VaR).

17 In Bessembinder et al (2009), four distinct strategies are used to compute daily prices from TRACE data: using the last price reported in TRACE for the day (“last price, all trades”), construct daily prices by weighing each trade by size (“trade-weighted price, all trades”), eliminating all trades below $100,000 dollars and using the last available price of the day (“last price, trade ≥ 100k”), and eliminating all trades below $100,000 and weighing each trade by size (“trade-weighted price, trade ≥ 100k”). Even though we do apply a “trade-weighted price, all trades” in this paper, we do exclude trades below $10,000 from our sample following Bai, Bali and Wen (2019).

18 This includes the coupon rate, the dated date marking the start of the interest period, as well as the interest frequency.

VaR measures how the proportion by which the price of an asset could decline over a certain period of time as a result of variations in market rates or prices. As an example, if the studied period is 10 days, and the probability of such an event is 5%, the VaR estimate would consist of evaluating the decline of an asset's value that could occur with 5% probability over the next 10 days. In order to determine a measure for VaR, we refer to the work of Bai, Bali and Wen (2019), in which the proxy for downside risk is a 5% VaR computed by selecting the second lowest monthly return distribution in a 36-month period. The result is then multiplied by -1 for convenience.

Table 1

Panel A: Traditional Bonds - Cross-sectional statistics over the sample period June 2002 - March 2019

				Percentiles					
	N	Mean	Median	5th	10th	25th	75th	90th	95th
Bond return (%)	1530745	0.51	0.34	-3.17	-1.75	-0.37	1.38	2.91	4.36
Rating	1530745	8.86	8.00	2.67	4.00	5.67	10.33	15.00	18.33
Time to maturity (maturity, year)	1530745	9.68	6.52	1.47	1.95	3.49	13.18	23.67	27.13
Size ($million)	1530745	380.10	250.00	1.99	4.48	19.57	500.00	1000.00	1250.00
Downside risk (5% VaR)	713984	3.73	2.52	0.53	0.84	1.46	4.24	7.58	11.79
Illiquidity (ILLIQ)	975447	2.36	0.58	0.03	0.05	0.17	1.65	4.02	7.46
Bond market beta (βbond)	908834	0.95	0.71	0.00	0.06	0.25	1.32	2.11	2.75

Panel B: Climate Bonds - Cross-sectional statistics over the sample period January June 2002 - March 2019

				Percentiles					
	N	Mean	Median	5th	10th	25th	75th	90th	95th
Bond return (%)	17356	0.40	0.30	-2.59	-1.53	-0.40	1.22	2.47	3.45
Rating	17356	8.54	8.50	6.00	6.50	7.50	9.00	10.33	12.00
Time to maturity (maturity, year)	17356	14.52	9.02	1.87	2.78	5.11	23.55	28.58	29.82
Size ($million)	17356	447.60	350.00	147.50	200.00	250.00	600.00	750.00	1000.00
Downside risk (5% VaR)	9492	2.59	2.16	0.66	0.93	1.39	3.49	4.68	5.51
Illiquidity (ILLIQ)	13199	1.66	0.55	0.04	0.07	0.20	1.46	3.26	5.33
Bond market beta (βbond)	12162	0.95	0.75	0.05	0.11	0.31	1.36	2.21	2.58

4.2. Credit quality

Credit ratings have been developed in order to assess bond default probabilities. Bond-specific ratings synthesize information relative to the issuer's financial condition, operating performance as well as risk management strategies and information relative to bond characteristics such as coupon rate and seniority. We collect credit ratings for our sample, as well as historical credit rating changes through the FISD database. We refer to credit ratings by S&P, Moody's and Fitch rating agencies. All credits ratings are assigned a number from 1 (AAA or Aaa) to 10 (BBB- or Baa3) for investment-grade bonds and numbers above 10 for non-investment grade bonds. Bond ratings in our datasets correspond to the average available credit ratings for each bond. We follow the numbering methodology provided by the FISD database and number bonds that have not been rated by either of the three rating agencies with a value of 27.

4.3. Bond Liquidity

The relationship between liquidity and corporate bond returns is well established. Empirical results have established the specific correlation between corporate bond yield spreads and bond liquidity (Chen et al., 2007; Dick-Nielsen et al., 2012). The bond-level liquidity measure developed by Bao et al. (2011) explains a significant proportion of the variations in bond yield spreads, and the market level liquidity measure developed by Lin et al. (2011) show that market liquidity beta is priced in corporate bond returns. Following Bai, Bali and Wan (2019), we chose to construct the bond-level liquidity measure developed by Bao et al. (2011) using our dataset through the following model:

The authors define as a bond's clean price (meaning the price of a bond without accounting for accrued interests and coupon payment) of the bond at time t and as the log price, and assume that consists of the following components :

$$p_t = f_t + u_t$$

Where represents the fundamental value of the log price in the absence of friction, and is generated from the impact of illiquidity. Therefore, in the author's framework, characterizes illiquidity on the market.

Finally, the authors define their measure for illiquidity, which is aimed at extracting this component in the observed clean log price , as follows:

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

With $\Delta p_t = p_t - p_{t-1}$. Bao et al. (2011) develop this model under the assumption that follows a random walk, so that only depends on and therefore increases when increases.

4.4. Bond market β

As we continue to refer to Bai, Bali and Wen (2019) to develop our bond risk factors, we compute the bond market excess return (MKTBond) by subtracting the one-month Treasury bill rate from the the value-weighted average returns of each corporate bond in our dataset. Therefore, for each bond-month in our dataset, we estimate the bond market beta (βBond) using a time-series regression of each bond's excess return on MKTBond using a 36-month rolling window.

4.5. Summary Statistics

Table 1 reports the cross-sectional statistics of both the entire corporate bond market sample and the climate bond market sample. Our total sample is composed of 1,530,745 bond returns. Our sample contains the same amount of data for credit rating, time-to-maturity and size. However, given the fact that our risk measures are obtained using specific computation processes, we have less observations for downside risk, illiquidity and bond market beta. Computing downside risk requires that a bond be issued at least 36 months before obtaining the first possible measure, illiquidity risk needs a minimal number of transactions or daily prices every month to be computed, and we compute the bond market beta using a 36-month rolling regression, which also require 36 month of data availability. Our total number of climate bond monthly returns consists in 17,356 observations, and observations in terms of downside risk, illiquidity risk and bond market beta are also sparser, specifically for downside risk for which we only have 9492 observations.

A few differences can be noticed between the two samples. Mean returns for the market are slightly higher in average than the climate bond market (0.51 for the market sample against 0.40 for climate bonds), even though median returns are almost similar (0.34 and 0.30 respectively). Climate bonds have higher time-to-maturity (14.52 years in average) and size ($447.62 million in average) than the corporate bond market (9.68 years to maturity and $380.10 million in size). Even though credit ratings for the market and for climate bonds are quite similar when looking at both mean and median ratings, climate bond rating experience much less variation across the sample : at the 5th percentile, climate bond credit ratings correspond to an A rating while at the 95th percentile, climate bond credit ratings correspond to BB/Ba2, while the market goes from between AA+/Aa1 and AA/Aa2 at the 5th percentile to between CCC/Caa and CCC-/Caa3 at the 95th percentile. Average illiquidity for the market is higher than for climate bonds, even though median liquidity is similar for both samples. Quite logically, climate bonds have lower value-at-risk (2.59 in average) than the market (3.73 in average) since they also have lower average returns. Finally, bond market betas are quite similar for climate bonds and the market (0.95 in average for both samples).

5. Downside risk and next-month excess returns

In this section we examine the specific relationship between downside risk and corporate bond returns through portfolio analysis. Throughout the rest of this study, we refer to the Newey-West adjusted t-statistic (Newey and West, 1987) to measure and indicate the statistical significance of our results. The Newey-West estimator was developed to overcome autocorrelation and heteroskedasticity in the error terms of models, in most cases for regressions that are applied to time series data. Since this study mostly relies on performing cross-sectional regressions and computing time series averages that are quite likely to have correlated error terms over time, the use of estimators such as the Newey-West estimator is required to demonstrate robust statistical significance.[19]

5.1. Univariate portfolio analysis

In order to perform our first portfolio analysis – the univariate portfolio analysis – we form quintile portfolios for every month between July 2005[20] and March 2019 by sorting corporate bonds according to their downside risk values. Quintile 1 contains bonds with the lowest VaR values, while quintile 5 contains bonds with the highest VaR values. The portfolios are weighted using size as weights. Table 2

19 This specific subject is addressed in Petersen (2009).

20 Even though we study TRACE data from July 2002 to March 2019, developing our measure for value-at-risk required at least 36 months of previous monthly returns, which means that our values for VaR can only be obtained from July 2005 onwards.

shows the average VaR for each quintile as well as average next-month excess returns[21]. This allows to illustrate the relationship that exists between downside risk and future returns. As the average VaR grows from 0.82% for quintile 1 to 4.77% for quintile 5, we observe a similar phenomenon for next-month average bond excess returns which grow from 0.11% to 0.37%. The difference between high Var portfolios and low VaR portfolios is both economically and statistically significant with an average next-month excess return difference of 0.26% and t-statistic of 5.10.

Table 2

Panel A - Corporate Bond market univariate portfolios

Quintiles	Average VaR	Average return	Stock Factors alpha	Bond Factors alpha	All Factors alpha	Average Portfolio Characteristics				
						Bbond	ILLIQ	Rating	Maturity	Size
Low VaR	0.82	0.11	0.10	0.09	0.09	0.34	0.15	6.90	3.21	370.48
		3.06	*3.06*	*3.22*	*2.27*					
2	1.50	0.18	0.16	0.14	0.14	0.54	0.30	7.29	4.74	414.49
		3.45	*2.79*	*3.12*	*3.23*					
3	2.21	0.23	0.21	0.19	0.19	0.74	0.47	7.92	7.36	390.86
		3.67	*3.13*	*3.52*	*3.37*					
4	3.11	0.28	0.26	0.22	0.23	0.96	0.63	8.10	11.54	397.51
		3.97	*3.43*	*3.99*	*3.56*					
High Var	4.77	0.37	0.34	0.32	0.32	1.27	0.78	8.99	15.32	392.07
		4.91	*4.28*	*4.73*	*4.43*					
High-Low	3.95***	0.26***	0.25***	0.23***	0.23***					
	22.08	*5.10*	*4.64*	*4.43*	*4.40*					

Panel B - Climate Bond univariate portfolios

Quintiles	Average VaR	Average return	Stock Factors alpha	Bond Factors alpha	All Factors alpha	Average Portfolio Characteristics				
						Bbond	ILLIQ	Rating	Maturity	Size
Low VaR	0.90	0.15	0.13	0.12	0.12	0.32	0.18	8.40	5.32	367.44
		2.85	*3.10*	*2.59*	*2.85*					
2	1.60	0.21	0.18	0.15	0.15	0.55	0.41	8.78	6.26	404.60
		3.68	*3.22*	*2.52*	*2.19*					
3	2.20	0.24	0.22	0.21	0.21	0.72	0.48	8.75	8.43	506.50
		3.78	*3.46*	*2.74*	*2.79*					
4	2.93	0.28	0.25	0.21	0.21	0.92	0.61	8.54	14.89	482.19
		2.80	*2.65*	*2.61*	*2.52*					
High Var	4.41	0.34	0.31	0.25	0.28	1.26	0.81	8.38	21.00	429.19
		3.66	*3.04*	*2.29*	*2.49*					
High-Low	3.52***	0.19**	0.18**	0.13	0.16*					
	15.69	*2.53*	*2.23*	*1.52*	*1.86*					

In addition to providing the next-month average excess return for every quintile, we also use control variables to understand if this relationship can be explained by other factors that have previously been developed in the literature. We regress next-month portfolio excess returns on the well-known stock market factors. These are the excess-stock market return (MKTstock), the size factor (SMB), the book-to-market factor (HML), the profitability factor (RMW), the investment factor (CMA), the momentum factor (MOM) and the liquidity risk factor (LIQ), which have been developed and computed in Fama and French (1993), Carhart (1997) and Pastor and Stambaugh (2003)[22]. We once again obtain

21 To compute excess returns, we subtract the risk-free rate from corporate bond returns. We use the risk-free measure available on Kenneth French’s website https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

22 Much like the risk-free rate, the excess-stock market return (MKTstock), the size factor (SMB), the book-to-market factor (HML), the profitability factor (RMW), the investment factor (CMA), the momentum factor (MOM) and the liquidity risk

economically and statistically significant stock alphas, which grow from an average of 0.10% for the lowest VaR quintile to 0.34% for the highest VaR quintile, with an economically and statistically significant difference of 0.25% in terms of return difference and a t-statistic of 4.64.

We also regress the next-month portfolios excess returns on well-known bond market factors: the bond market excess return (MKTbond), the term factor (TERM) and the default factor (DEF). We obtain the default factor (DEF) by computing the difference between the monthly returns of a market portfolio of long-term corporate bonds and monthly long-term government bond returns, and the term factor (TERM) by computing the difference between monthly long-term government bond returns and the risk-free rate. Much like for our stock market factors, we obtain statistically significant alphas that grow as the downside risk grows. Finally, we also perform a regression of the next-month portfolio excess returns on all our factors. Our results are economically and statistically significant when regressing on our bond factors and on all our factors combined, with a difference in returns of 0.23% for both type of regressions, and t-statistics of 4.43 and 4.40 respectively.

Finally, we also compute the averages for the market beta, illiquidity, rating, maturity and size for each VaR quintile and observe that some relations might also exist between next-month excess bond returns and some of these variables. Average bond market beta grows from an average of 0.34 for VaR 1 to 1.27 for VaR 5, illiquidity goes from an average of 0.15 to 0.78, and time-to-maturity grows from an average of 3.21 years to 15.32 years with VaR. The existence of such relation is less clear regarding size, as growth of average size for VaR quintiles is not constant, even though size does grow from 370.48 million in average for VaR 1 to 392.07 million for VaR 5. Credit rating diminishes[23] as value-at-risk grows for the market, with credit ratings going from 6.90 (which approximately corresponds to an A-/A3 rating) for the lowest VaR quintile to an 8.99 (which approximately corresponds to a BBB/Baa rating) for highest Var quintile.

Comparing our results for the market sample with the results for the climate bond sample, we do observe some differences in terms of statistical significance, as none of the differences between Var 1 and Var 5 in terms of next-month excess return or alphas have a statistical significance at the 1% level. More specifically, the bond factor alpha is strictly not statistically significant, even though the difference in average alphas for cross-sections with all factors alphas is statistically significant at the 10% level. This lower statistical significance could be attributed to the fact that there are much less bond observations in our climate bond sample, which could lead to less significant results. Economic significance in returns and alphas between average VaR 1 quintile portfolios and VaR 5 quintile portfolios is lower for climate bonds with 0.19% in average excess return difference and 0.16% when controlling for the ten stock and bond market factors. This is not surprising given the fact that climate bonds in our sample have both lower average returns and lower downside risk than the market sample. Finally, average portfolio characteristics for our climate bond sample behave in a similar fashion than for the market sample with regards to bond market beta, illiquidity, maturity and size, while the relationship between VaR, excess return and credit rating seems to disappear as credit rating for VaR 1

factor (LIQ) can be found online, either on Kenneth French's website https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ or Lubos Pastor's website https://faculty.chicagobooth.edu/lubos-pastor/research

23 Our credit ratings are ranked from 1 to 27, 1 being the best possible rating (AAA or Aaa) and 27 being the worst. Therefore, as our value for credit rating grows, it illustrates a worsening of the actual credit risk of the bond.

and for Var 5 are similar (8.40 and 8.38 respectively). This could in part be explained by the lack of variation in credit ratings within our climate bond sample.

Following Bai, Bali and Wen (2019), these apparent interactions between downside risk and other variables leads us to test whether the relationship between downside risk and returns holds when controlling for market beta, credit rating, maturity, liquidity and size using both a bivariate portfolio analysis and Fama-Macbeth (1973) bond-level regressions.

5.2. Bivariate portfolio analysis

Table 3 exposes the results of our bivariate portfolio analysis. Much like for the previous univariate analysis, we sort our bonds monthly according to specific characteristics. However, the process here is a bit different, as we first sort bonds according to either credit rating (Panel A), maturity (Panel B), size (Panel C) or liquidity (Panel D) into five different quintiles. Once this initial process has been performed, we further sort each quintile into five quintiles based on downside risk. We therefore have 25 distinct portfolios per month, and each portfolio has very similar characteristics while downside risk maintains some dispersion. We compute value-weighted average returns for each portfolio. Much like the univariate sort, portfolios are weighted using size as weights. We then compute average returns for every VaR quintile category (portfolios with the highest VaR quintile being Var quintile 5 and the lowest being Var quintile 1). We therefore have five portfolios per month corresponding to each VaR category. We perform time series regressions for each of these monthly portfolios using the 10 stock and bond factors previously computed for our univariate portfolio analysis. Much like it was the case for our univariate sorts, we refer to the Newey-West adjusted t-statistic for statistical significance.

As we can see from our results, the relationship between downside risk and next month excess returns holds for every characteristic, both for our market sample and our climate bond sample after controlling for the ten stock and bond market factors. Looking at the market sample, difference between VaR 5 portfolios and VaR 1 portfolios are both economically and statistically significant, with differences of 0.19% when controlling for credit rating, 0.15% when controlling for maturity, 0.18% when controlling for size and 0.15% when controlling for liquidity, with each result having a statistical significance at the 1% level. Results for the climate bond sample only vary slightly, with lower economic significance for differences in excess returns when controlling for credit rating (0.13%) and maturity (0.07%) and overall lower statistical significance, as the difference in excess returns when controlling for size is the only one that has a statistical significance at the 1% level.

5.3. Bond-level Fama-MacBeth regressions

Once we have tested the relationship between downside risk and corporate bond returns through portfolio analyses, we perform bond-level analysis through the application of Fama-Macbeth (1973) regressions. The Fama-MacBeth procedure consists in running a cross-sectional regression every month in order to obtain monthly coefficients, and then perform a time series average to obtain average coefficients for the entire time period considered. Once again, in this procedure, the use of Newey-West adjusted t-statistics is essential to establish statistical significance. Following Bai, Bali and Wen (2019) we perform ten distinct Fama-French regressions, regressing each factor individually and with control variables and then regressing all four factors with and without control variables. Our control variables are bond exposure to both the term factor (β^{TERM}) and the default factor (β^{DEF}), time-to-maturity, size and lagged excess return. Table 4 shows the results for the bond-level Fama-MacBeth regressions.

In regression (1), the average slope coefficients of monthly regressions of excess bond returns on VaR without control variables is 0.078 with a t-statistic of 4.90. The economic significance of this effect resembles that of the univariate portfolio analysis in which we found a spread of 3.95 for our VaR values between low Var and high Var portfolios. Multiplying this spread by the slope coefficient, we obtain a monthly downside risk premium of 30 basis points. Slope coefficients for regressions (3), (5) and (7), which correspond to the regressions of excess bond returns on credit rating, illiquidity and market beta individually and without control variables, are also positive and statistically significant. This also corresponds to our results for the univariate portfolio analysis, in which we can observe a positive difference between low Var quintiles and high Var quintiles in terms of average credit rating, illiquidity and bond market beta.

Performing these same regressions but controlling for beta term, beta default, maturity, size and lagged excess returns does not change our results. Controlling for these characteristics maintains significantly positive and significant results for all our risk variables and does not affect their positive relation with next-month bond returns. Surprisingly, however, controlling for these factors even enhances our results for regressions (2), (4) and (8).

Our results diverge slightly for Bai, Bali and Wen (2019) when all our variables are regressed together. In regression (9), though our VaR measure is still positive and statistically significant, our liquidity measure is neither economically nor statistically significant, but our credit rating measure is. However, when controlling for our different bond characteristics in regression (10), economical and statistical significance for credit rating disappears and illiquidity becomes positive and statistically significant. Much like Bai, Bali and Wen (2019), statistical significance for bond market beta disappears for both regression (9) and (10), and the return reversal control variable is very significant statistically and has a negative relation with next-month excess return. Finally, we observe that many of our control variables are statistically significant when regressing variables independently. More specifically, bond exposure to the default factor is always both positive and statistically significant at the 1% level. This is also the case for bond exposure to the term factor for regressions (4) and (6).

Regarding our climate bond sample (Panel B), our bond-level Fama-Macbeth regression analysis is limited by the lack of monthly data available for our climate bond sample[24], and we are only able to perform individual regressions without control variables. This is sufficient however to detect positive and statistically significant slope coefficients for regression of one-month ahead excess return on VaR (1), illiquidity (3) and bond market beta (4) and that no such results are obtained for the regression of one-month ahead excess returns on credit rating (3). These results correspond to results obtained in our

24 Our number of monthly observations for Climate Bonds have a median value of 61, while it can be considered as a rule of thumb that 10 to 20 observations are needed per estimated parameter (Harrell,2015). This would mean that in order to perform any of the regressions with control variables, a strict minimum of 60 observations are required.

univariate portfolio analysis for the climate bond sample, where we established a positive statistically significant difference in terms of VaR between VaR 5 portfolios and VaR 1 portfolios, but also observed such positive differences for average quintile liquidity and average bond market beta, while this relation did not exist for our average credit ratings. Much like it was the case for the univariate portfolio analysis, this result could well be due to the lack of variation in terms of credit ratings in our climate bond sample. Furthermore, by multiplying our slope coefficient of 0.072 for regression (1) by the difference in downside risk in our univariate portfolio analysis of 3.52%, we obtain a monthly down-side risk premium for climate bonds of 27,5 basis points, slightly under our results for the market sample.

Table 4

Panel A - Bond-level Fama-MacBeth cross-sectional regressions (Market)

	Intercept	5% VaR	Rating	ILLIQ	BBond	BDEF	BTERM	Maturity	Size	REV	Adj. R2
(1)	**0.446**	**0.078**									0.025
	60.516	*4.899*									
(2)	**0.363**	**0.080**				**0.322**	0.079	0.016	-0.017	**-0.185**	0.158
	2.408	*6.592*				*4.621*	*0.524*	*0.647*	*-1.630*	*-28.493*	
(3)	**0.484**		**0.034**								0.022
	61.602		*3.535*								
(4)	-0.026		**0.071**			**0.594**	**0.558**	0.087	-0.037	**-0.191**	0.165
	-0.161		*5.488*			*4.657*	*2.733*	*3.057*	*-3.143*	*-28.118*	
(5)	**0.484**			**0.026**							0.018
	81.291			*3.747*							
(6)	-0.239			**0.021**		**1.032**	**0.542**	**0.082**	0.017	**-0.164**	0.176
	-1.282			*3.868*		*5.438*	*2.259*	*2.604*	*1.131*	*-30.171*	
(7)	**0.472**				**0.018**						0.035
	92.110				*5.808*						
(8)	**0.399**				**0.068**	**0.289**	**0.064**	**0.067**	**-0.033**	**-0.188**	0.158
	2.794				*4.782*	*2.776*	*0.309*	*2.356*	*-2.900*	*-28.801*	
(9)	**0.424**	**0.057**	**0.045**	0.009	0.029						0.112
	56.756	*6.299*	*2.747*	*1.471*	*1.303*						
(10)	0.252	**0.062**	0.010	**0.056**	0.025	0.223	0.221	0.000	0.000	**-0.174**	0.214
	1.678	*7.908*	*1.842*	*3.830*	*0.958*	*1.467*	*1.423*	*0.004*	*0.025*	*-46.298*	

Panel B - Bond-level Fama-MacBeth cross-sectional regressions (Climate Bonds)

	Intercept	5% VaR	Rating	ILLIQ	BBond	BDEF	BTERM	Maturity	Size	REV	Adj. R2
(1)	**0.448**	**0.072**									0.083
	56.660	*2.404*									
(2)	**0.478**		0.039								0.020
	40.930		*1.329*								
(3)	**0.484**			**0.026**							0.046
	71.040			*2.386*							
(4)	**0.464**				**0.026**						0.094
	21.020				*2.495*						

6. Common risk factors in the cross-section of climate bond returns

6.1. Determining the bond-level risk factors

In order to construct our bond factors, we follow Fama and French (2015) and rely on independent sorts. To construct the downside risk factor for corporate bonds, for each month from July 2004 to December 2016, we form bivariate portfolios by independently sorting bonds into five quintiles based on their credit rating and five quintiles based on their downside risk (measured by 5% VaR). The downside risk factor, DRF, is the value-weighted average return difference between the highest-VaR portfolio and the lowest-VaR portfolio across the rating portfolios. The credit risk factor, CRF VaR, is the value-weighted average return difference between the lowest-rating (i.e., highest credit risk) portfolio and the highest-rating (i.e., lowest credit risk) portfolio across the VaR portfolios. The liquidity risk and the return reversal factors are constructed similarly using independent sorts. The liquidity risk factor, LRF, is the value-weighted average return difference between the highest-illiquidity and the lowest- illiquidity portfolios across the rating portfolios. The return reversal factor, REV, is the value-weighted average return difference between the short-term loser and the short- term winner portfolios (losers-minus-winners) across the rating portfolios. The above independent sorts used to construct LRF and REV produce two additional credit risk factors, CRF ILLIQ and CRF REV. The credit risk factor CRF is defined as the average of CRF VaR , CRF ILLIQ , and CRF REV .

Table 5

Panel A - Bond factors (summary statistics)		
	Mean	t-stat
MKTbond	0.58	3.28
Downside risk factor (DRF)	0.22	4.11
Liquidity risk factor (LRF)	0.18	3.50
Credit risk factor (CRF)	0.44	11.93
Return reversal factor (REV)	0.14	2.44

Panel B - Bond Factors (ten-factor alpha)		
	Alpha	t-stat
Downside risk factor (DRF)	0.19	3.40
Liquidity risk factor (LRF)	0.14	2.43
Credit risk factor (CRF)	0.10	1.73
Return reversal factor (REV)	0.43	10.99

As table 5 reports, over our sample period the corporate bond market risk premium (MKT^{Bond}) is 0.58% per month with a t-statistic of 3.28 and the value-weighted downside risk factor (DRF) has an economically and statistically significant risk premium of 0.22% with a t-statistic of 4.11. All other risk factors are also economically and statistically significant : our liquidity risk factor (LRF) has a risk premium of 0.18% with a t-statistic of 3.60, our credit risk factor (CRF) has a risk premium of 0.44% with a t-statistic of 11.93 and our return reversal factor (REV) has a risk premium of 0.14 with a t-stat of 2.44.

We then explore whether the stock and bond factors used to test our results in our univariate and bivariate portfolio analyses participate in explaining our bond-specific factors. We use the exact same factors to compute factors alphas in table 5. These consist of seven stock factors that are the excess-stock market return (MKTstock), the size factor (SMB), the book-to-market factor (HML), the profitability factor (RMW), the investment factor (CMA), the momentum factor (MOM) and the liquidity risk factor (LIQ) and three bond factors that the bond market excess return (MKTbond), the term factor (TERM) and the default factor (DEF).

Our factor alphas are also positive and statistically significant. Our ten-factor alpha for the downside risk factor is of 0.19% with a t-statistic of 3.40, our alpha for the liquidity risk factor is of 0.14% with a t-statistic of 2.43, our alpha for the credit risk factor is of 0.10% with a lower statistical significance of 1.73 and our return reversal factor is of 0.43% with a t-statistic of 10.99. Overall, these results demonstrate that that the ten stock and bond factors previously developed by the literature do not explain the new bond-specific factors, which therefore capture a consequent proportion of corporate bond return variation.

6.2. Size/maturity-sorted and industry-sorted portfolios

Continuing to follow Bai, Bali and Wen (2019), we apply the authors' most performant model – the four-factor model composed of the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF) and the bond specific liquidity factor (LRF) – to both size/maturity-sorted portfolios and industry-sorted portfolio.

Though our results differ from the authors', the four-factor model, when applied to our dataset, results in an average adjusted R-square of 0.49 for size/maturity-sorted portfolios and 0.50 for industry-sorted portfolios, and outperforms other models proposed by Bai, Bali and Wen (2019). However, results for the four-factor model do differ in our case, since we obtain a positive and statistically significant average alpha of 0.15 with a t-statistic of 3.99 for size/maturity-sorted portfolios of the market sample. In addition, model performance, when using adjusted R-square as a measure, seems to increase as maturity increases. This leads the four-factor model to obtain an adjusted R-square of 0.91 for the portfolio containing the largest and most mature bonds (size quintile 5 and maturity quintile 5). This pattern is also recognizable in our size/maturity-sorted portfolio constructed from the climate bond sample. Looking at industry sorted portfolios, we notice some industries have much higher adjusted R-squared than others. As an example, the "Electric" and "Transportation" industries having adjusted R-squared of 0.76 and 0.74 respectively, while industries such as "Water" and "Savings and Loans" have adjusted R-squared of 0.26. Similar differences can be observed in our climate bond sample. Results for our size/maturity-sorted portfolios and industry-sorted portfolios are available in table A1 and A2 of the Appendix.

7. Conclusion

The literature on the common risk factors of bond returns is still quite scarce, and Bai, Bali and Wen (2019) are the first to identify bond factors conceptualized from the specific profile of bond investors. Their study could well be the first of a series of studies on the cross-section of US corporate bonds that refer to rich bond-specific databases such as TRACE and FISD in order to obtain more precise information and results on the market.

First and foremost, this paper participated in this literature by exploring the authors' methodology in depth in order to examine if results of this previous research were replicable. Overall, we obtain very positive results on the relationship between downside risk and next-month excess-bond returns, and the Bai, Bali and Wen's four-factor model performs very well on size/maturity- and industry-sorted portfolios.

Furthermore, the specific methodology develop by the authors give us a favorable framework to study our sample of climate bonds and allows us to understand if these financial products behave differently than their more "traditional" equivalents. We notice some dissimilarities, but overall climate bonds seem only to represent a small, specific sample of the overall US corporate bond market.

We consider this study only as a first step towards understanding how climate-aligned firms behave. As urgency regarding climate adaptation and mitigation grows, so will transparency on the environmental impact of business activities and the firms that participate in these activities. This will undoubtedly start to impact how these firms are viewed by investors in the market. In this sense, this paper established preliminary work for future research in this field.

Lastly, as financial economists are starting to question the dense literature on the "zoo of factors" that have been discovered to explain the cross-section of stock returns and the methodologies that are used to determine such factors, there seems to be a need for more advanced and robust statistical tools in financial economy, the likes of which could well be provided by machine learning statistical approaches and learning methods.

Appendix

A.1 Size/Maturity-sorted portfolios

Panel A - Explanatory power of factor models for size/maturity sorted portfolios (Market)

Maturity Quintile	Maturity Quintile	Alpha	t-stat	Adjusted R-squared
1	1	0.22	5.97	0.09
1	2	0.12	4.22	0.21
1	3	0.08	2.86	0.25
1	4	0.06	2.39	0.26
1	5	0.08	2.35	0.16
2	1	0.24	6.87	0.28
2	2	0.18	5.28	0.31
2	3	0.12	4.04	0.43
2	4	0.10	2.52	0.44
2	5	0.10	2.23	0.34
3	1	0.27	6.59	0.30
3	2	0.20	5.00	0.48
3	3	0.15	4.13	0.59
3	4	0.12	2.65	0.57
3	5	0.12	1.73	0.50
4	1	0.32	8.19	0.43
4	2	0.21	6.46	0.60
4	3	0.15	3.34	0.69
4	4	0.10	2.44	0.73
4	5	0.06	1.16	0.70
5	1	0.32	8.32	0.51
5	2	0.20	5.82	0.69
5	3	0.10	3.58	0.83
5	4	0.03	1.15	0.90
5	5	0.02	0.52	0.91
Average		**0.15**	**3.99**	**0.49**

Panel B - Explanatory power of factor models for size/maturity sorted portfolios (Climate Bonds)

Size quintile		alpha	tstat	adjR
1	1	0.06	0.96	0.17
2	1	0.13	3.61	0.32
3	1	0.10	2.16	0.33
1	2	0.05	0.92	0.38
2	2	0.22	2.60	0.47
3	2	0.04	0.54	0.62
1	3	0.02	0.33	0.50
2	3	0.09	1.51	0.63
3	3	0.03	0.59	0.72
Average		**0.08**	**1.47**	**0.46**

A.2 Industry-sorted portfolios

Panel A - Explanatory power of factor models for industry-sorted portfolios (Market)

Industry Code	Description	Alpha	t-stat	Adjusted R-squared
10	Manufacturing	0.09	1.58	0.66
11	Media/Communications	0.07	1.43	0.64
12	Oil and Gas	0.05	0.88	0.56
13	Railroad	0.07	1.53	0.64
14	Retail	0.10	2.04	0.68
15	Service/Leisure	0.08	1.30	0.63
16	Transportation	0.08	1.52	0.74
17	Mining/Refining	0.01	0.04	0.45
20	Banking	0.08	1.18	0.50
21	Credit/Financing	0.10	1.60	0.43
22	Financial Services	0.06	0.74	0.42
23	Insurance	0.07	1.60	0.69
24	Real Estate	0.07	1.40	0.59
25	Savings And Loan	0.05	0.50	0.26
26	Leasing	0.18	2.56	0.29
30	Electric	0.08	1.63	0.76
31	Gas	0.06	1.05	0.57
32	Telephone	0.09	1.12	0.58
33	Water	0.08	1.15	0.26
40	Foreign Agencies	-0.13	-0.98	0.24
42	Supranationals	0.12	1.87	0.27
44	U.S. Agencies	0.05	0.27	0.17
60	Miscellaneous	0.09	0.97	0.33
99	Unassigned	-0.03	-0.35	0.59
	Average	**0.07**	**1.11**	**0.50**

Panel B - Explanatory power of factor models for industry-sorted portfolios (Climate Bonds)

Industry Code	Description	Alpha	t-stat	Adjusted R-squared
10	Manufacturing	-0.01	-0.23	0.54
13	Railroad	0.07	1.44	0.65
16	Transportation	0.12	2.07	0.71
30	Electric	0.21	1.76	0.34
26	Leasing	0.07	1.15	0.29
33	Water	0.12	1.39	0.25
	Average	**0.10**	**1.26**	**0.46**

References

Anton, W.R.Q., Deltas, G. and Khanna, M., 2004. Incentives for environmental self-regulation and implications for environmental performance. *Journal of environmental economics and management*, *48*(1), pp.632-654.

Bachelet, M. J., Becchetti, L., & Manfredonia, S. (2019). The green bonds premium puzzle: The role of issuer characteristics and third-party verification. *Sustainability*, *11*(4), 1098.

Bai, J., Bali, T.G. and Wen, Q., 2019. Common risk factors in the cross-section of corporate bond returns. *Journal of Financial Economics*, *131*(3), pp.619-642.

Bao, J., Pan, J. and Wang, J., 2011. The illiquidity of corporate bonds. *The Journal of Finance*, *66*(3), pp.911-946.

Barney, J., 1991. Firm resources and sustained competitive advantage. *Journal of management*, *17*(1), pp.99-120.

Bhattacharyya, A. and Cummings, L., 2015. Measuring corporate environmental performance–stakeholder engagement evaluation. *Business Strategy and the Environment*, *24*(5), pp.309-325.

Bessembinder, H., Kahle, K.M., Maxwell, W.F. and Xu, D., 2008. Measuring abnormal bond performance. *The Review of Financial Studies*, *22*(10), pp.4219-4258.

Buchner, B., Herve-Mignucci, M., Trabacchi, C., Wilkinson, J., Stadelmann, M., Boyd, R., Mazza, F., Falconer, A. and Micale, V., 2013. Global landscape of climate finance 2015. *Climate Policy Initiative*.

Busch, T. and Friede, G., 2018. The robustness of the corporate social and financial performance relation: A second-order meta-analysis. *Corporate Social Responsibility and Environmental Management*, *25*(4), pp.583-608.

Chen, L., Lesmond, D.A. and Wei, J., 2007. Corporate yield spreads and bond liquidity. *The Journal of Finance*, *62*(1), pp.119-149.

Climate Bonds Initiative, 2018. Bonds and Climate Change: The State of the Market.

Council of the European Union, 2019. “Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL on the establishment of a framework to facilitate sustainable investment - Approval of the final compromise text”

Delmas, M.A., Etzion, D. and Nairn-Birch, N., 2013. Triangulating environmental performance: What do corporate social responsibility ratings really capture?. *Academy of Management Perspectives*, *27*(3), pp.255-267.

Dick-Nielsen, J., 2009. Liquidity biases in TRACE. *The Journal of Fixed Income*, *19*(2), pp.43-55.

Dick-Nielsen, J., 2014. How to clean enhanced TRACE data. *Available at SSRN 2337908*.

Dick-Nielsen, J., Feldhütter, P. and Lando, D., 2012. Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics*, *103*(3), pp.471-492.

Donaldson, T. and Preston, L.E., 1995. The stakeholder theory of the corporation: Concepts, evidence, and implications. *Academy of management Review*, *20*(1), pp.65-91.

Escrig-Olmedo, E., Muñoz-Torres, M.J., Fernández-Izquierdo, M.Á. and Rivera-Lirio, J.M., 2017. Measuring corporate environmental performance: A methodology for sustainable development. *Business Strategy and the Environment*, *26*(2), pp.142-162.

European Commission (2018) *Action Plan: Financing Sustainable Growth*.

EU Technical Expert Group on Sustainable Finance, 2020. “Taxonomy: Final report of the Technical Expert Group on Sustainable Finance.”

Fama, E.F. and MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, *81*(3),pp.607-636.

Fama, E.F. and French, K.R., 2015. A five-factor asset pricing model. *Journal of financial economics*, *116*(1), pp.1-22.

Flammer, C., 2018. Corporate green bonds.

Friede, G., Busch, T. and Bassen, A., 2015. ESG and financial performance: aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, *5*(4), pp.210-233.

Friedman, M., 1970. September 13. The social responsibility of business is to increase its profits. *New York Times Magazine*, *33*, p.126.

Ge, W. and Liu, M., 2015. Corporate social responsibility and the cost of corporate bonds. *Journal of Accounting and Public Policy*, *34*(6), pp.597-624.

GSIA, 2018. Global Sustainable Investment Review, GSIA Report, April.

Hachenberg, B. and Schiereck, D., 2018. Are green bonds priced differently from conventional bonds?. *Journal of Asset Management*, *19*(6), pp.371-383.

Hartmann, J. and Vachon, S., 2018. Linking environmental management to environmental performance: The interactive role of industry context. *Business Strategy and the Environment*, *27*(3), pp.359-374.

Jostova, G., Nikolova, S., Philipov, A. and Stahel, C.W., 2013. Momentum in corporate bond returns. *The Review of Financial Studies*, *26*(7), pp.1649-1693.

Kapraun, J. and Scheins, C., 2019. (In)-Credibly Green: Which Bonds Trade at a Green Bond Premium?. *Available at SSRN 3347337*.

Kotsantonis, S. and Serafeim, G., 2019. Four Things No One Will Tell You About ESG Data. *Journal of Applied Corporate Finance*, *31*(2), pp.50-58.

Lin, H., Wang, J. and Wu, C., 2011. Liquidity risk and expected corporate bond returns. *Journal of Financial Economics*, *99*(3), pp.628-650.

Linklaters, 2019. Sustainable Finance. The rise of green loans and sustainability linked lending.

Markowitz, H., 1959. *Portfolio selection: Efficient diversification of investments* (Vol. 16). New York: John Wiley.

Misani, N. and Pogutz, S., 2015. Unraveling the effects of environmental outcomes and processes on financial performance: A non-linear approach. *Ecological economics*, *109*, pp.150-160.

Newey, W.K. and West, K.D., 1986. A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix.

Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, *22*(1), pp.435-480.

Polbennikov, S., Desclée, A., Dynkin, L. and Maitra, A., 2016. ESG ratings and performance of corporate bonds. *The Journal of Fixed Income*, *26*(1), pp.21-41.

Porter, M.E. and Kramer, M.R., 2006. The link between competitive advantage and corporate social responsibility. *Harvard business review*, *84*(12), pp.78-92.

Post, C., Rahman, N. and McQuillen, C., 2015. From board composition to corporate environmental performance through sustainability-themed alliances. *Journal of Business Ethics*, *130*(2), pp.423-435.

Ren, S., He, D., Zhang, T. and Chen, X., 2019. Symbolic reactions or substantive pro-environmental behaviour? An empirical study of corporate environmental performance under the government's environmental subsidy scheme. *Business Strategy and the Environment*, *28*(6), pp.1148-1165.

Sarig, O. and Warga, A., 1989. Bond price data and bond market liquidity. *Journal of Financial and Quantitative Analysis*, *24*(3), pp.367-378.

Schiereck, D., Friede, G. and Bassen, A., 2019. Financial Performances of Green Securities. In *The Rise of Green Finance in Europe* (pp. 95-117). Palgrave Macmillan, Cham.

SIFMA, 2019. Capital Markets Fact Book 2019.

Trumpp, C., Endrikat, J., Zopf, C. and Guenther, E., 2015. Definition, conceptualization, and measurement of corporate environmental performance: A critical examination of a multidimensional construct. *Journal of Business Ethics*, *126*(2), pp.185-204.

Trumpp, C. and Guenther, T., 2017. Too little or too much? Exploring U-shaped relationships between corporate environmental performance and corporate financial performance. *Business Strategy and the Environment*, *26*(1), pp.49-68.

Xie, S. and Hayase, K., 2007. Corporate environmental performance evaluation: a measurement model and a new concept. *Business Strategy and the Environment*, *16*(2), pp.148-168.

Xue, B., Zhang, Z. and Li, P., 2020. Corporate environmental performance, environmental management and firm risk. *Business Strategy and the Environment*, *29*(3), pp.1074-1096.

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