

MALD Capstone

**Is carbon risk a determinant of corporate bond
credit risk? Focus on the U.S. utilities sector**

Submitted to Professor Kelly Sims Gallagher
Written with the support of Professor Patrick Schena

Lisa Tessier

In fulfillment of the MALD capstone requirement

April 13th, 2016



THE FLETCHER SCHOOL
OF LAW AND DIPLOMACY
TUFTS UNIVERSITY

CONTENTS

Abstract 5

I. Introduction..... 6

II. Conceptual framework..... 8

 1) Corporate bond market, credit risk and rating 8

 2) Climate and carbon risks definition 10

 3) Impact of GHG emissions on credit quality 14

 4) High exposure of the electric utilities companies to carbon and credit risk 16

III. Related literature and hypothesis development 18

 1) Responsible investment literature 18

 2) Hypotheses 21

IV. Data and methodology 22

 1) Data sources and sample selection..... 22

 2) Variables 23

 3) Descriptive statistics 25

 4) Empirical methodology..... 31

V. Results and discussion 34

 1) Regression results 34

 2) Discussion 41

 3) Implications..... 42

VI. Conclusion 43

Acknowledgments 44

Appendix 45

References 47

List of Acronyms

AUM: Assets under management

BP: Basis points

CCS: Carbon Capture and Storage

CDP: Carbon Disclosure Project

CO₂: Carbon dioxide

CO_{2eq}: Carbon dioxide equivalent

COP: Conference of the Parties

CSR: Corporate Social Responsibility

CTI: Carbon Tracker Initiative

EIA: Energy Information Administration

ESG: Environment, Social and Governance

EPA: Environmental Protection agency

GHG: Greenhouse Gases

Gt: Gigaton (or million ton)

IEA: International Energy Agency

IOC: International Oil Company

KLD: Kinder, Lynderberg, Domini Research & Analytics

LIBOR: London Interbank Offered Rate

PRI: Principles for Responsible Investment

RGGI: Regional Greenhouse Gas Initiative

RI: Responsible investment

S&P: Standard and Poor's

UNEP FI: United Nations Environment Programme Finance Initiative

UNFCCC: United Nations Framework Convention on Climate Change

List of figures

Figure 1: Corporate criteria framework to evaluate issuer credit rating (S&P, 2015).....	9
Figure 2: 14 Sectors identified by Moody's with Very High or High Credit Exposure to Carbon Regulations (Moody's 2015).....	17
Figure 3: Average Scope1 GHG emissions intensity of the sample companies per sector	30

List of tables

Table 1: Sample selection process	22
Table 2: Summary of the variable names, description, units and expected correlation with credit spread	25
Table 3: Bond-level descriptive statistics.....	26
Table 4: Issuer-level descriptive statistics.....	26
Table 5: Descriptive statistics by industry	28
Table 6: OLS regression results with the credit spread as dependent variable	34
Table 7: OLS regression results with the credit spread as dependent variable and year interactions	36
Table 8: OLS regression results with the credit spread as dependent variable and Utilities interactions	39
Table 9: Credit Rating regression results	Erreur ! Signet non défini.
Table 10: Recoding credit rating classifications	45
Table 11: Issuer-level descriptive statistics weighing the number of bonds issued over the time period.....	46

Abstract

Climate change is an increasing concern in financial markets due to the uncertainties arising from its physical impacts and to the consequences of climate mitigation on our economies. This paper aims at analyzing whether carbon risk is a determinant of corporate bond credit risk in the United States, with a particular focus on the utilities sector, which is the most carbon-intensive sector in the country. For the purpose of this study, carbon risk entails risks faced by carbon extractors and emitters emerging from potential future climate liabilities or from regulatory and technological changes associated with the transition to a low-carbon economy. The fundamental hypothesis underlying the analysis is that carbon risk can affect the solvency of carbon-intensive borrowers by exposing them to costly legal and regulatory risk. An empirical econometrics study was realized to test this theory. Carbon intensity – defined as greenhouse gas emissions per sales – was used as a proxy for carbon risk, and bond credit spread was used as a measure of credit risk. We conduct our investigation using a sample of 1,075 bonds issued between 2010 and 2015 by 144 companies across all sectors of the U.S. economy. Although the results found no average impact of carbon risk on credit spread for new bond issues over the whole sample period, a deeper analysis revealed that carbon risk did not impact credit spread in the early years of this study (2010 through 2013), but had a small-to-moderate impact in 2014 and a non-existent-to-small impact in 2015. The dataset did not permit to get any conclusive results on the differential impact of carbon risk on credit spread for the utilities sector. These findings shed light on how financial actors in the United States account for carbon risk, providing information useful to issuing companies and institutional investors.

I. Introduction

Climate change is an unprecedented challenge to our planet and societies. Although the magnitude and geographical location of climate impacts continue to be debated and researched, there is scientific consensus that climate change is caused by anthropogenic greenhouse gas (GHG) emissions; and that it will radically affect our planet's ecosystems and economies, most profoundly through rising sea-levels, increased droughts and heat waves, more frequent extreme weather events, and changing mortality patterns (IPCC, 2014). For the first time in history, a global climate deal was signed at the 21st Conference of the Parties to the United Nations Convention on Climate Change (UNFCCC) in Paris (COP21) in December 2015, reaffirming the goal of limiting global temperature rise well below 2°C, and urging efforts to limit the increase to 1.5°C. In particular, the agreement required that all UNFCCC parties – industrialized as well as developing countries – prepare and communicate National Determined Contributions to climate mitigation and adaptation, with a legally binding mechanism to increase such contributions every five years. The agreement reaffirmed the current goal of mobilizing \$100 billion annually in climate finance by 2020 to support developing countries' efforts, and extends this target through 2025. Further, it aims to establish a more aggressive goal for the period after 2025 (UNFCCC, 2015).

Over the past decade, the financial sector has been paying increasing attention to climate change and the long-term financial risks that will arise both from changes in the global climate regime and from socio-economic changes associated with a transition to a low-carbon economy (Labatt and White, 2007; CTI, 2011; Carney, 2015). In particular, to better evaluate their exposure to climate change, investors increasingly demand that firms assess and disclose their relative climate and carbon risks. This paper will focus on carbon risk, defined as the risks faced by carbon extractors and emitters emerging from potential future climate liabilities or from regulatory and technological changes associated with the transition to a low-carbon economy. There is an emerging consensus amongst academics and professionals that firms, in particular the most carbon-intensive ones, are significantly exposed to carbon risk (Jung et. al, 2014).

In the United States, the largest source of GHG emissions is carbon dioxide (CO₂) from fossil fuel combustion, which accounted for approximately 77% of the nation's emissions between 1990 and 2013. The most carbon-intensive sector, electricity generation, emitted approximately 31% of the U.S. GHG emissions in 2013, driven by the country's large

dependence on fossil fuels, which represented 67% of the electricity mix in 2015 – within which coal represented 33% and natural gas 33% (EPA, 2015; EIA, 2016).

In this paper, we investigate the incorporation of carbon risk in the U.S. corporate bond market, and its impact on credit risk for new bond issues, in particular within the power generation (or utilities) sector. The U.S. bond market is the largest securities market in the world and plays a crucial role in the global and U.S. economy. Bonds are one way that public or private institutions can borrow funds to develop new projects or infrastructure through financial markets, usually at lower cost than through banks. The borrower (issuer of the bond) makes a legal promise to repay the amount back to the bondholder on a specific future date (maturity date), plus interest, at a periodic rate. Investments in bonds have multiplied since the beginning of the 21st century, and today the U.S. bond market exceeds \$34 trillion. This paper will focus specifically on the corporate bond market, which represented \$7.54 trillion in debt outstanding in 2013. Investors in corporate bonds include both individuals and large financial institutions such as pension funds, endowments, mutual funds, insurance companies, and banks. Yields (bond interest rates) among corporate bonds can differ substantially based on the perceived credit risk of the individual corporation and the profitability and competitiveness of its sector (SIFMA, 2013). The conceptual framework of this paper is based on the view that carbon risk influences the credit risk of individual corporations, thereby affecting the yield of their corporate bonds. An econometrics model will be used to evaluate this theory, using data from new bonds issued in the United States between 2010 and 2015.

This paper will contribute to the Responsible Investment literature, generally aiming to analyze the impacts of taking into account Environment, Social, and Governance (ESG) criteria in corporate strategy and investment processes on financial performance. The literature evaluates the impact of ESG criteria on three main categories of financial indicators: corporate financial performances, investment returns, and the cost of capital. This paper will contribute to the latter category. Although the impact of ESG indicators on corporate financial performance and company valuation has been widely studied, fewer studies have examined the impact on the cost of capital and in particular on the cost of debt, hence the focus of this paper on this topic (Deutsche Bank, 2012). The implications of this analysis are relevant both for corporations, whose goal is to minimize their cost of capital, and for institutional

investors, in particular insurance companies and pension funds, which are key actors in the corporate bond markets (Trusted Sources, 2011).¹

The paper will first present the conceptual framework and define the key terminology of corporate bond markets and carbon risk. Then, an overview of the related literature will be provided, along with the development of the key hypotheses. The paper will then describe the data used for the analysis and the construction of the empirical model. Finally the results will be presented and discussed, in light of the existing literature.

II. Conceptual framework

1) Corporate bond market, credit risk and rating

A major source of funds for firms worldwide is the international bond market, where corporations can issue bonds, long-term debt ranging from 1 to 30 years of maturity. Corporate bonds are first issued in the primary corporate bond market, usually facilitated through the services of an investment bank that can provide expertise on the yield and maturity of the security. Then an investment bank, or a syndicate formed by the bank, usually acts as an intermediary to buy the bond and sell it back to institutional investors. As a liquid security, the bond can then be sold in the secondary bond market from one investor to another until it matures.

The **yield of the bond** – the rate of return required by bondholders – gives information about the default risk taken by the investors, which is the risk that the companies will be unable to make the required payments on their debt obligations. The bond spread or **credit spread** – as it will be referred to in this paper – is the difference between a bond's yield and the yield on a similar Treasury bond. Thus the credit spread represents the extra returns required by bondholders above the risk-free rate, which is an estimate of the default risk premium, also called **credit risk premium** (Brigham and Ehrhardt, 2011). Different corporate bonds have different levels of credit risk, assessed by rating agencies, dependent on the issuing company's characteristics and the terms of the specific bond.

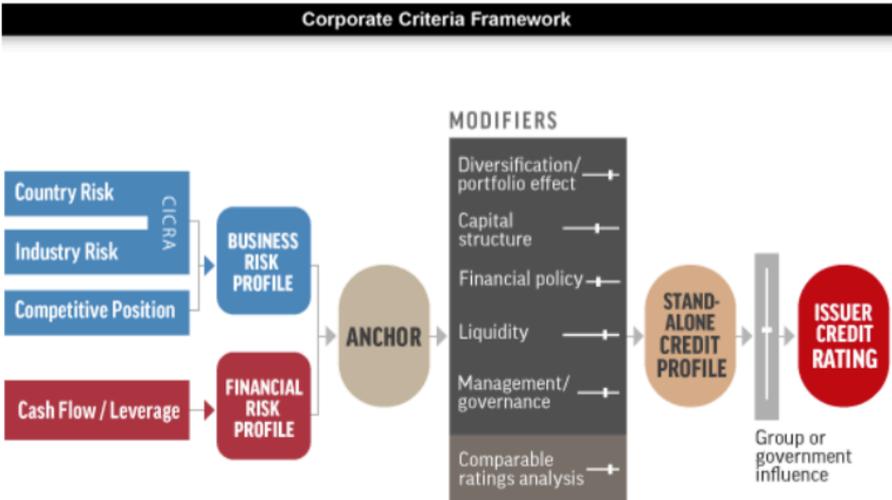
¹ In the United States, the insurance sector and to a lesser extent the pension funds have played a major role in deepening the corporate bond market.

The following paragraphs provide an overview of the relationship between issuer rating, issue rating and bond yield, to set the context of how carbon risk might influence corporate bond yields.

Issuer Rating

Rating agencies incorporate several criteria related to the business and financial health of the company to evaluate its risk profile and issue a rating. For example, Standard and Poor’s (S&P) assesses the corporate business risk profile through a combination of assessments of the company’s industry risk, country risk, and competitive position. S&P then assess the financial risk profile by a cash flow analysis and a leverage analysis – examining the ratio between the company’s debt and the value of its common stock (equity). Additional factors such as financial policy, liquidity, management and governance are used to adjust the risk profile. Figure 1 provides a visual summary of S&P’s general framework to assess issuer rating. In addition, S&P applies complementary industry-specific criteria where Environmental and Climate (E&C) risks are material enough to affect the company’s credit risk. Those E&C risks can be reflected in the business risk through industry risk, or in the competitive position – for example being ahead of environmental regulations can give a competitive advantage. E&C risk can also be captured through the “management and governance modifier” – reflecting whether management deals appropriately with such risks (S&P, 2015).

Figure 1: Corporate criteria framework to evaluate issuer credit rating (S&P, 2015)



Issue rating

Issue rating assesses the creditworthiness of a specific financial obligation. It is tied both to the default risk of the issuer and ultimate recovery prospects of the issue itself. Ultimate recovery prospects are dependent on factors including the seniority of debt – order of repayment in the event of a sale or bankruptcy of the issuer – or collaterals that are attached to the debt as additional guarantee for the bondholder (Feinland Katz, 2008).

Corporate bond yield

While bond ratings are established by rating agencies, bond yields are established in competitive trading marketplaces. Corporate bond yield represents the consensus price that investors are willing to pay for a bond on a particular day considering the overall risk inherent to the security reflected by the rating. Studies on the relationship between financial variables, bond ratings and bond yields indicate that certain financial variables have incremental explanatory power for bond yields, beyond the information included in bond ratings. This implies that financial data has information content not completely captured by the bond ratings and exert an influence on bond yield both directly and indirectly through bond rating (Ederington et al., 1987; Reiter and Ziebart, 1991; Ziebart and Reiter, 1992). Thus corporate bond yield could reflect extra information on how the corporate bond market perceives the investment risks.

In that framework, the following paragraphs define carbon risk and lay out the theory of how carbon risk can influence issuer rating and bond yield.

2) Climate and carbon risks definition

Financial risks arising from climate change

The financial risks arising from climate change mitigation and from the physical impacts of climate change have been studied seriously by members of the financial sector for years, especially reinsurers (Brauner, 2002; CII, 2009), and are increasingly documented in the literature. In September 2015, Mark Carney, Governor of the Bank of England and chairman of the Financial Stability Board, gave a speech on the major threats to financial stability posed by climate change. Defining climate change as a tragedy of the horizons, he pointed out the inconsistency between the short-termism of monetary policy and credit cycle, and the long-term impacts of climate change on financial stability. He highlighted the three major channels

through which climate change can impact financial stability, and in particular the insurance sector (Carney, 2015):

- **Physical risks:** the impacts, already happening, on insurance liabilities and the value of financial assets that arise from climate-related events, such as floods and storms that damage property or disrupt supply chains and trade;
- **Liability risks:** the impacts that could arise in the future if parties who have suffered loss or damage from the effects of climate change seek compensation from those they hold responsible. Such claims could come decades in the future, but have the potential to hit carbon extractors and emitters – and, if they have liability cover, their insurers;
- **Transition risks:** the financial risks that could result from the process of adjustment towards a lower-carbon economy; including changes in policy and technology.

For the purpose of this study, purely physical risks from climate change are set aside. I will focus specifically on **carbon risk**, entailing the liability risks and transition risks defined previously (Chenet and Dupré, 2013).

Sources of carbon risk

Major determinants of the carbon risk are historic and cumulative GHG emissions, current GHG emissions, and future potential GHG emissions tied to energy companies' fossil fuel reserves.

➤ *Liability risk*

The scientific and political focus on climate policy, and growing losses attributed to climate change are having a profound impact on climate litigation. Climate litigation entails the long-term risk that lawsuits targeting companies with high cumulative past emissions create liabilities, based on the company's share of responsibility in the cost of climate change. Such litigation is likely to occur in countries where class action exists such as the United States, where lawsuits are an inevitable part of the system for determining whether and how to compensate for damages (Chenet et Dupré, 2013). Both public and private nuisance theory could be used in climate litigation. Public nuisance theory is well suited to address climate change because the impacts affect public rights (health, safety, use of property); and state plaintiffs could seek compensation from GHG emitters for damages such as sea-level rise or permafrost-melt, and planning and adaptation costs resulting from the changing climate. Private nuisance lawsuits could be filed against large GHG emitters by individuals injured by

the physical impacts of climate change (property damage in low-lying coastal areas for example) (Ross et al., 2007). Such climate litigation is already underway:

- In 2004, eight States, the city of New York, and three land trusts separately sued American Electric Power Company and four other American power companies under public nuisance law, due to ongoing contributions to global warming; demanding that the companies reduce their CO₂ emissions (*American Electric Power Co v. Connecticut, 2010*).
- In 2008, a native Alaskan village, Kivalina, sought money for damages provoked by flooding from a group of oil, utility and coal companies (including Peabody, AES, American Electric Power Company, and Duke Energy) under the theory that the defendants' GHG emissions constituted public nuisance (*Kivalina v. ExxonMobil, 2011*).

Although to date all cases are pending or have been dismissed, and the liability risk is still perceived as low probability, jurisprudence is evolving. The Heede Report published in 2013 showed that nearly 2/3 of total global GHG emissions were the responsibility of just 90 companies. This report helped assign the blame and individualize responsibility by giving a list with names and numbers (Zegart, 2014). Some legal experts believe that climate litigation is at a turning point and could follow the trajectory of the U.S. tobacco litigation, charging high-emitting companies for failing to act on their GHG emissions responsibly (Geiling, 2015).

➤ *Regulatory risk*

The most prominent source of risk, at least in the short and medium-term, is linked to the transition to a low-carbon economy, and arises from current and future carbon-related policy. Companies are increasingly compelled to internalize the cost of carbon emissions, either through market mechanisms such as cap and trade or carbon taxes, or through policies regulating emissions in carbon-intensive sectors like the power generation or vehicles sector (Chenet and Dupré, 2013). Regulatory exposure can come from the company's own operations (direct or Scope 1 emissions), from indirect emissions from the company's supply chain energy consumption (indirect or Scope 2 emissions), or from emissions linked to the use of a company's goods and services (other indirect or Scope 3 emissions). The power sector is one of the most vulnerable to this regulatory risk. Within the power sector, a company's generating assets, technology, fuel mix and market position shape the impact of

carbon regulation, and companies at greater risk are those producing from carbon-intensive coal (Labatt and White, 2007). In the United States, recent major state, regional, and national climate policies in the power generation sector have dramatically increased the carbon risk for carbon-intensive utilities:

- *Regional Greenhouse Gas Initiative – RGGI*: Since 2009, the six New England States as well as the states of New York, Delaware and Maryland have implemented a regional cap-and-trade program to reduce CO₂ emissions from power generation. Under cap-and-trade, a regional GHG emissions cap is set, trade permits or allowances are then issued, and can be traded among companies. From 165 million ton short of CO₂ emitted in 2009, RGGI's cap was set to 91 million short tons for 2014, with an annual reduction of 2.5 % each year through 2020 (RGGI, 2016).
- *California Cap-and-Trade program*: This program was set to help put California on the path to meet its goal of reducing GHG emissions to 1990 levels by 2020, and ultimately achieving an 80% reduction from 1990 levels by 2050. The cap-and-trade program came into effect in January 2013, and since the second compliance period started in 2015, covers 85% of the State's emissions, covering electricity generation, industrial sources, distribution of transportation fuel and natural gas. The program's cap is 334.2 million tons of CO_{2eq} in 2020 – representing a 15% reduction between 2015 and 2020 in the sectors covered (C2ES, 2016).
- *EPA Clean Power Plan*: On August 3rd, 2015, the U.S. Environmental Protection Agency (EPA) finalized, under authority of the Clean Air Act, the first standards to curb carbon emissions from power plants. The Plan targets new, modified and reconstructed power plants, locking the coal industry into decline. The Clean Power Plan establishes state-by-state goals for emission reductions and provides flexibility for states to meet their targets: states are free to choose among trading mechanisms, increase of coal plant efficiency, shifting coal generation to natural gas or renewable power generation, or demand-side measures. The Plan is expected to cut carbon emissions by 32% below 2005 levels by 2030, when it is fully in place. Although EPA finalized the Plan, there are still regulatory risks created by the uncertainty about how each state will implement it. In addition, the Plan was put on hold by the Supreme Court in February 2016, who questioned its legal justification, creating additional regulatory uncertainty (Stohr and Dlouhy, 2016).

On the international stage, the United States pledged to cut its emissions by 17% below 2005 levels by 2020 at COP15 in Copenhagen in 2009. More recently, the nation submitted its Intended Nationally Determined Contributions in the lead-up to COP21 in Paris, to reduce its net GHG emissions by 26–28% below 2005 in 2025. Some analysts argue that, although the finalized Clean Power Plan contributes to moving forwards the climate targets, the country will need to implement additional policies to meet its 2035 targets (CAT, 2015). Thus, forward-looking regulatory carbon risk is still present.

➤ *Stranded assets risk*

Carbon stranded assets are assets that may lose economic value before the end of their expected life, mainly because of changes in regulation, technology and market forces driven by the transition to a low-carbon economy. A core assumption is that policymakers and regulators will eventually adopt the necessary measures to keep the warming under 2°C compared to pre-industrial levels (MSCI, 2015; CTI, 2013). In addition to pure regulatory changes, the rapid development and falling costs of new technologies could also trigger large-scale substitution of current energy sources with cleaner energy sources. According to the IEA, restrictions on GHG emissions and technology substitution could imply that two-thirds of the fossil fuel reserves (oil, gas, and coal) that we have already discovered but not yet extracted could remain unused. Fixed assets reliant on burning fossil fuels, such as power plants, can also be financially affected if they are prematurely retired because of new regulations and/or a shift in energy technology, making them uneconomical to operate for their full-expected life (MSCI, 2015).

Although we expect stranded assets risk to have an impact on the creditworthiness of energy companies (for example through reduced future cash-flows of coal or mining companies), the direct analytical and quantitative link between the quantity of fossil fuel reserves – indicator of future GHG emissions – and the creditworthiness of a company is not straightforward. For this reason, we will focus only on risks related to current GHG emissions, with an emphasis on the utilities sector.

3) Impact of carbon intensity on credit quality

As explained later in the data and methodology section (IV), the proxy used in our study for carbon risk is carbon intensity, defined as GHG emissions per sales. The following section details the three channels – risks, performance, and investors reputation – through which high

carbon intensity at the time of the bond issuance can translate into altered credit rating and larger credit spread, in particular for utilities. The risk and performance channels are presented using the framework detailed in Figure 1.

1. Risks

Industry risk

Regulatory risk can result in future **drains on cash flows to comply with standards** through the adoption of new technology, or trading of emissions credits. Even further, carbon regulation in conjunction with adoption of new technologies could lead carbon-intensive power plants, such as coal-fired plants, to **retire** before their full-expected life, significantly hindering the company's ability to honor their debt obligations.

Business risk

Climate liabilities due to current levels of GHG emissions could reduce future cash flows, at minimum due to expensive legal fees, but potentially with significant compensation costs.

2. Performance, competitive position

A study by PricewaterhouseCoopers claimed that sustainability was emerging as a market driver with the potential to grow profits and present opportunities for value creation (PWC, 2010). In that respect, sustainable product or process innovation can therefore have substantial impacts on a company's revenues. In the case of our study, lower carbon intensity could imply a better strategic competitive advantage for companies that innovated in anticipation of future regulations through new products or processes using resources more efficiently. For example, in the airlines sector, an innovative company came up with a microbe as a natural biocatalyst that can capture CO₂ and turn it into ethanol for fuel, and believes that such innovations will assist airlines meet their carbon reductions targets, while making them more competitive (Clark et al., 2015). In the power generation sector, companies that have invested in technologies to improve the efficiency of their power generation processes (such as supercritical pulverized coal) increase at the same time the amount of power produced per fuel input and their carbon intensity. In addition, investing in recent technology to reduce carbon intensity can provide a first-mover competitive advantage.

3. Investors reputation

Finally, institutional investors and lenders are themselves increasingly scrutinized for their “financed emissions”, especially in the energy sector (Chenet and Dupré, 2013). For example, the Montreal Carbon Pledge, supported by the Principles for Responsible Investment (PRI) and the United Nations Environment Programme Finance Initiative (UNEP FI), was launched on September 25th, 2014. It is a commitment by investors to measure and publicly disclose the carbon footprint of their investment portfolios (or a portion of it) on an annual basis. In the lead up to COP21, investors with portfolios totaling \$3 trillion signed this pledge. As a further step, the Portfolio Decarbonization Coalition (PDC) aims to gather investors committing to decarbonize their portfolios. Now PDC convenes 25 investors overseeing the decarbonization of \$600 billion in Assets under Management (AUM), which is much higher than the \$100 billion target set for COP21 (PDC, 2016). The Carbon Disclosure Project (CDP) is also working with approximately 830 institutional investors holding more than \$100 trillion in AUM to help them reveal the environmental risks embedded in their investment portfolios, including carbon risks. For that purpose, they give investors access to a global source of information updated annually, and leverage investor’s shareholder power to encourage their investees to disclose their risks, and GHG emission in particular (CDP, 2016).

Although such reputational risk would not have an impact on the issuer or issue rating itself, it might be captured directly in the market with corporate bond yields. In this vein, Chava hypothesized and showed that environmentally sensitive lending can reduce the number of lenders for firms with environmental concerns, increasing thereby their cost of debt (Chava, 2011).

4) High exposure of utilities companies to carbon and credit risk

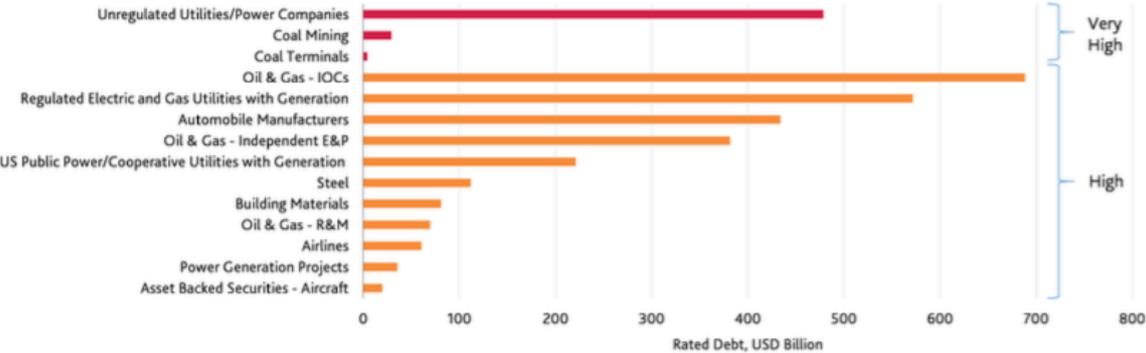
Electric utilities are particularly sensitive to carbon risk, resulting in altered credit risk, because they are high GHG emitters and usually carry high debt levels, as their infrastructure requirements make large, periodic capital expenditures necessary. Rating agencies have recently starting reporting the high exposure of electric utilities to carbon and credit risk.

S&P reviewed the cases in which Environmental and Climate (E&C) risks resulted in or contributed to a corporate rating revision, or have been a significant factor in their rating analysis. Across all of S&P’s global corporate rating actions and reports between November 2013 and October 2015, they identified 299 cases where E&C risks had a direct material

impact on credit quality – nearly 80% of which were negative in direction. The bulk of these ratings were in the oil refining and marketing, regulated utilities and unregulated power and gas sectors. S&P forecasts that rating actions linked to E&C factors could accelerate in coming years (S&P, 2015).

At the conclusion of COP21, **Moody’s** issued a report stating that the Paris Agreement would advance the adoption of carbon and other GHG emission regulations, with increasing credit implications for many sectors globally. As illustrated in Figure 2, the rating agency identified 14 sectors – accounting for approximately \$3.2 trillion of rated debt – where the credit implications of carbon regulations were material: unregulated and regulated utilities/power generation companies, coal mining, coal terminals, oil and gas (upstream and downstream sectors), automobile manufacturers, steel, building materials, airlines, and asset backed securities aircraft. Three sectors – unregulated power generation, coal mining, and coal terminals – have a very high credit exposure to carbon regulations, emerging from increased regulation in the absence of substantial counter-balancing initiatives. The unregulated/power companies have by far the highest amount of rated debt among those three sectors (Moody’s, 2015).

Figure 2: 14 Sectors identified by Moody’s with Very High or High Credit Exposure to Carbon Regulations (Moody’s 2015)



Note: Qualitative scoring assessment of the credit exposure of a given sector to carbon regulations. The scoring was part of a heat map developed by relevant Moody’s analytical teams and Moody’s credit policy group. The review took place on a globally coordinated basis from September to November 2015.
 Source: Moody’s Investors Service

III. Related literature and hypothesis development

1) Responsible investment literature

The majority of studies looking specifically at the impact of environmental factors on the cost of debt have found that environmental concerns increased the cost of debt and conversely that good environmental performance lowered the cost of debt (Clark et. al, 2015). A few studies, however, have found either opposite results or did not observe statistically significant results (Sharfman and Fernando, 2007; Menz, 2010; Chava, 2011).

Two studies have focused specifically on the impact of carbon emissions on the cost of debt. Chen and Gao looked at the impact of carbon emission rates on the cost of equity and the cost of debt of publicly traded U.S. electric utilities between 2002 and 2008. For the cost of debt, the scope of their study was the secondary bond market, and they looked specifically at the impact of carbon emissions on the bond yield to maturity. The paper found that carbon emission rates have a positive and significant impact on the cost of debt – whereby an increase by 1 ton/MWh increases the bond yield by 1.4 to 2.5 percentage points (Chen and Gao, 2012).² Jung et. al studied the impact of firms’ carbon risk profiles on the cost of debt in Australia over the period 2009-2013. Their cost of debt measure reflected the interest expense incurred by a company in a specific year divided by the amount of interest-bearing debt in the previous year. They measured carbon risk exposure in a year with recent historical GHG emissions (previous year) and carbon risk awareness based on the willingness of the company to respond to CDP questionnaires. They found that (i) there was a statistically significant relationship between firms higher carbon risk exposure and higher cost of debt: an increase in carbon intensity by one standard deviation (0.0014 tons of CO₂ per thousand dollar of sales) increased the average loan interest rates by 17% to 25%; and (ii) firms could mitigate this carbon risk “penalty” to their cost of debt by providing evidence regarding their awareness of the carbon risks that they faced, measured as their reporting to CDP (Jung et. al, 2014).

Several papers also looked at the impact of an array of environmental factors, including climate exposure, on the cost of debt. Bauer and Hann assessed the impact of environmental management performance on credit risk for 582 public corporations in the United States

² I would treat the results by Chen and Gao with cautious though, as the article exhibits weaknesses in my opinion: lack of transparency on the units in the result tables and absence of economical interpretation to analyze the regression results; very low R² in all their regression models. Finally, they use the same variables for the equity and bond models, which is not consistent with the theory.

between 1995 and 2006. They modeled several measures of credit risk: credit spread (at issue), credit rating and issuer rating. For environmental performance, they looked separately at environmental concerns indicators – aggregating performance on factors including hazardous waste or climate change risk exposure – and environmental strengths indicators – aggregating information on companies’ pollution prevention policy or use of clean energy (KLD indices³). Their major findings were that (i) environmental concerns were associated with a higher cost of debt financing and lower credit ratings – the corporate activities underlying this relation being mainly related to regulatory and climate change issues; (ii) proactive environmental practices were associated with a lower cost of debt and a higher bond rating; (iii) environmental risks played a more prominent role for rating agencies when assessing the general creditworthiness of companies than proactive environmental practices; (iv) the relevance of environmental concerns for credit risk had increased over time (Bauer and Hann, 2010). Chava examined the impact of environmental performance on the cost of capital for 1,341 firms in the United States between 1992 and 2007. For the cost of debt, he focused on the bank loan spreads (variation of interest rates over LIBOR rates). For environmental performance they used the same indicators of environmental concerns and strengths as in Bauer and Hann (KLD indices), as well as a measure of aggregate environmental performance and an additional climate score defined as: climate risk exposure - clean energy use. They found that banks charged firms with environmental concerns a higher loan interest rate (statistically significant). On the contrary, they found that the impact of environmental strengths on lower interest rates was not statistically significant. Their climate score was associated with higher interest rates, but unlike Bauer and Hann was not statistically significant, indicating that lenders are not factoring the net climate exposure of a firm in setting debt interest rates (Chava, 2011).

Finally, additional studies looked at the impact of other environmental factors or Corporate Socially Responsibility (CSR) indicators on the cost of debt. Among them, Graham and Maher examined the relationship among bond ratings and bond yields, and various estimates of a firm’s contingent environmental remediation liability – measured by EPA’s assessment of cost remediation. The study focused on new bond issues of U.S. companies between 1995

³ KLD indices are environmental indicators created by Kinder, Lynderberg, Domini Research & Analytics (now MSCI), an independent investment research company specialized in the assessment of firms’ environmental management, social performance, and corporate governance standards. In the Environment dimension, KLD lists qualitative performance indicators of company’s environmental strengths (e.g. use of clean energy) and environmental concerns (e.g. hazardous waste or climate risks).

and 1998. They found that external EPA-based estimates of a firm's environmental obligations were significantly associated with a firm's bond rating, providing relevant incremental information beyond that supplied by the environmental accruals presented in the firm's financial statements. Furthermore, they showed that the external EPA-based estimates provided an indirect effect on bond yield through their impact on bond rating (Graham and Maher, 2006). Schneider analyzed environmental performance as a determinant of bond pricing in two of the most polluting industries in the United States: the pulp and paper, and chemical industries. The paper used bond yield to maturity as the measure of bond pricing, and the Toxic Release Inventory (TRI) to quantify environmental performance – indicating the level of future potential environmental liabilities and cleanup costs. He showed that firms with inferior environmental performance had higher bond yields than those firms with relatively better environmental performance, and that the relationship decreased as the bond quality increases (Schneider, 2010). Sharfman and Fernando studied the relationship between environmental risk management and the cost of capital, in particular the firm's marginal cost of borrowing, for 267 U.S. companies. Environmental performance was based on Toxic Release Inventory (TRI) data and KLD indices. They found that the overall cost of capital (including cost of equity) was negatively correlated with environmental risk management, but that contrary to their initial hypothesis, companies that managed their environmental risks faced a higher cost of debt. Several explanations for such results were provided. First, debt markets may continue to see investments in environmental risk management beyond what is necessary as inefficient. If institutional debt holders evaluate strictly on current risks, long-term investments in environmental risks management may appear as risky in the short term. An alternative explanation was that environmental risk management could increase the ability of companies to take on debt, increasing thereby their leverage and thus their cost of debt. It is then possible that the effect of higher leverage on the cost of debt could not be separated from the effect of environmental risk management (Sharfman and Fernando, 2007). Finally, Menz looked more broadly at the impact of Corporate Social Responsibility (CSR) on corporate bond credit spread. It was the first study looking at the European bond market, with data from the period 2004-2007. He found no statistical significance to validate his main hypothesis that good CSR ranking decreases the credit spread (Menz, 2010).

This paper will add to the literature focusing on the impacts of climate and carbon risks on credit risk that is very scarce.

2) Hypotheses

Hypothesis 1: Companies with higher carbon intensity face a higher credit risk.

As explained in the conceptual framework and generally shown in the literature, we expect environmental concerns to increase credit risk. In particular, higher carbon intensity could increase the carbon risks from regulatory and climate liability risk, investor reputation, and competitive position risks. Thus we expect carbon intensity to have a positive impact on credit spread.

Hypothesis 2: The impact of carbon intensity on credit risk has increased over time between 2010 and 2015.

Over the 2010-2015 sample period, we have witnessed increasing scientific evidence on the impacts and causes of climate change with the release of the 5th IPCC report in 2014, accrued climate policy making at state, national, and international levels, increasing awareness of the civil society that can impact both climate litigation risk and investor reputational risk, increasing awareness of the financial sector on climate and carbon risks, and changing methodologies by rating agencies to account for environmental and climate risks in credit rating. We therefore expect that the impact of carbon intensity on credit risk increased over time between 2010 and 2015. In line with this assumption, Bauer and Hann reported an increase in the relevance of environmental management performance for in the credit risk over time (Bauer and Hann, 2010).

Hypothesis 3: The impact carbon intensity on credit risk is higher for utilities than for all other sectors

Since the utilities are at the same time the largest carbon emitting companies (EPA, 2015), the sector with highest credit exposure to carbon regulation (Moody's, 2015), and among the sectors issuing the more debt (see Figure 2, and summary statistics in IV.0, we expect the impact of carbon intensity on credit spread to be higher for utilities as compared with other sectors.

IV. Data and methodology

1) Data sources and sample selection

The sample is comprised of 1,075 new bond issues between January 1st 2010 and December 21st, 2015 in the United States. The time frame was chosen to start in 2010 to avoid potential biases due to the 2008 financial crisis. Company data and corporate bond data were collected from the Bloomberg database and then combined into one single dataset.⁴ To combine both databases, I matched company data with bond data according to the time of the year when the bond was issued. For bonds issued in the first three quarters before the end of the company's fiscal year (for instance from January 1st to September 30th if the fiscal year ends in December), I matched the bond with financial and emissions data from the previous year, knowing that such information is available publicly through the previous year annual report. Conversely, for bonds issued in the last quarter (after October 1st for companies which fiscal year ends in December), I matched them with data from the end of the current year. Indeed, I assumed that for bonds issued in the last quarter, the financial and emissions data from the current year would represent more accurately the credit risk, and that such information would be available to the rating agencies and the bond underwriters before published in annual reports. A detailed overview of the selection process is summarized in Table 1.

Table 1: Sample selection process

	Number of observations
Total corporate bonds issued in the Unites States between 1/1/2010 and 12/21/2015	32,637
<i>Less:</i> bonds with special features (callable, convertible, putable, sinkable)	16,734
<i>Less:</i> bonds without data for either Treasury spread at issue or yield at issue (dependent variable)	3,668
<i>Less:</i> bonds without rating at issue from any of the three major rating agencies: Moody's, S&P and Fitch (control variable)	3,526
<i>Less:</i> bonds for which the issuer did not have total GHG emissions per sales data for 2014 (independent variable of interest) ⁵	1,075

⁴ Bond data were collected from the "SRCH" function in Bloomberg that can provide many characteristics on the bond itself, as well as the latest available financial or ESG characteristics of the issuing company (in this case, the 2014 data). The sample selection was made through the "SRCH" function. To collect financial and ESG characteristics for several years for the issuing company, I used another function (Excel Bloomberg add-in).

⁵ Since I could only use 2014 data to narrow down the sample, I assumed that companies that did not report their GHG emissions in 2014, likely had not reported them either the years before.

2) Variables

The credit risk analysis incorporates three sets of variables that previous studies have identified as determinants of credit risk, accounting for macro-level factors, issuer characteristics and bond characteristics.

1) Dependent variable

Credit spread: corporate bond yield at issuance, normalized by subtracting the risk-free rate at time of issue for similar maturity bonds, expressed in basis points (bp). When collecting the data, I either had access to credit spread directly or to bond yield at issue. For bonds for which the Treasury spread at issue (or credit spread) was not available, I calculated manually the credit spread by subtracting the U.S. Treasury bond yield of similar maturity, traded on the same day. Daily U.S. Treasury bond yield was collected from the U.S. Department of the Treasury website (U.S. Department of the Treasury, 2016). For the bonds whose original maturity fell between two of the benchmark treasury bonds, (for example 15 years, falling between the 10 and 20 years benchmarks), I used linear interpolation to apply an appropriate weighting of the benchmarks. As explained previously, the credit spread reflects the premium that the market charges issuers for assuming the risk that the company may default on its debt obligation.

2) Independent variable of interest

Two measures of carbon intensity are used as proxies of the carbon risk. **Scope 1 GHG** represents direct GHG or CO₂ emissions as reported by the companies in their publicly available reports, normalized by dividing by the sales revenue. **Total GHG** represents the sum of Scope 1 (direct) and Scope 2 emissions (indirect emissions through the energy supply chain) as reported by the companies, similarly weighted by the sales revenue. Both measures of carbon intensity are reported in metric tons of CO_{2eq} per million dollar of revenue. As presented in our hypotheses, we expect those variables to be positively correlated with the credit spread.

3) Control variables

- Macroeconomic level characteristics:

We use the 10-year bond Treasury yield on the day of the bond issuance as a proxy for the general **interest rate** at the moment of issue.⁶ Higher interest rates are a sign of economic growth, and we expect credit spread to be negatively correlated with high interest rates due to the close relation between economic growth and the risk-free rate (Tang and Yan, 2010; Citibank, 2013).

- Company-level characteristics:

The **size** of the company, defined as the log of total assets, is an important determinant of the financial strength, with higher total assets being consistent with lower credit spread. The degree of **leverage**, defined here as total debt divided by total assets, represents an important risk factor for bondholders, with higher leverage associated with higher credit risk. The **Industry** (or sector) in which the company operates is defined with the Bloomberg Industry Classification System (BICS).

- Bond-level data:

The **maturity** refers to the original maturity in years of the bond at the time of issue. Longer maturities are usually associated with higher credit risk because of higher uncertainty in the further future about the company and macroeconomic conditions or regulatory environment. The variable **amount** issued is defined as the log of the initial amount issued by the company. The expected relation between the issue size of a bond and its default risk is ambiguous. Indeed, large debt issues are generally associated with higher liquidity, and thus are expected to reduce the issue yield spread. However, large debt obligations also imply a higher default probability for the bond issuer and higher expected absolute loss for the bondholder (Bauer and Hann, 2010). **Rating** is a measurement of the bond credit rating. We prioritized Moody's ratings when they were available. When they were not, we used in priority S&P ratings, and if the latter were not available, we used Fitch ratings. We then created a discrete scale to convert ratings in the form of letters (AAA, BB+) into numbers, following the approach used in Bauer and Hann, 2010 (see Appendix 1 Table 9). The codes were assigned so that a higher rating indicates better credit quality (AAA is coded as 6, and B- is coded as 1). The discrete numbers were then logged in order to create the final rating variable. The variable was created in such a way that we expect higher rating to be associated with lower credit spread. The

⁶ Another reason to use the 10-year Treasury yield is that the average maturity of the sample size is 10 years (see section IV.0).

functional form created by logging the bond rating allows for a decreasing impact of rating on credit spread as bond rating increases. Indeed, we can expect lower ratings of 1 and 2 in the non-investment grade category to have a bigger impact on credit spread than ratings in the investment grade category.

Table 2: Summary of the variable names, description, units and expected correlation with credit spread

Variable name	Description of the variable	Unit	Expected sign of correlation with the credit spread
Dependent variable			
Spread	Credit spread: corporate bond yield minus treasury yield of same maturity at the time of issue	Basis points (bp)	/
Macroeconomic level variables			
Interest	10-year Treasury yield on the day of the bond issuance	%	-
Year	Year		NA
Emissions variables			
Scope1 GHG	Direct carbon intensity measured as Scope 1 or direct GHG emissions per sales	Metric tons of CO _{2eq} per million \$ ⁷	+
Total GHG	Total Carbon intensity measured as total GHG emissions (Scope 1+Scope 2) per sales	Metric tons of CO _{2eq} per million \$	+
Company level variables			
Size	Log of Total Assets	log(million \$)	-
Leverage	Total Debt to Total Assets	%	+
Industry	Sector in which the company operates	NA	NA
Bond level variables			
Rating	Bond rating		-
Amount	Log of original amount of issuance	log(million \$)	?
Maturity	Original maturity	Years	+

3) Descriptive statistics

Table 3 and Table 4 present the summary statistics of all the regression variables, at the bond-level and issuer level. The variables that are logged in the model (*Size*, *Rating* and *Amount*) are reported in real values to facilitate interpretation.

⁷ Abbreviated tCO_{2eq}/\$M in the rest of the paper

Table 3: Bond-level descriptive statistics

Variable	Number of observations	Mean	Standard deviation	Median	Minimum	Maximum
Dependent variable						
Spread	1,075	127.03	109.68	105	-1.49	946
Control variables						
Rating	1,059	3.65	0.86	4	1	6
Amount (million \$)	1,072	1,010.0	969.78	750	0.218	15,000
Maturity	1,075	9.59	8.45	7.00	1.98	99.99
Macroeconomic level variable						
Interest	1,074	2.41	0.56	2.29	1.44	3.91

The bond statistics confirm that the sample is meaningful and representative. Indeed, the average *Spread* is 127 basis points and there is significant variation in this dependent variable, with a standard deviation of 109 basis points, and a range of 947 basis points between the minimum and maximum credit spreads. The median rating is 4, which corresponds to ratings between A+ and A- (or A1 and A3 for Moody's ratings); and only 4% of the bonds have a rating below investment grade (BBB- or Baa3). The average issue size is \$1,010 million and the average original maturity is approximately 10 years.

Table 4: Issuer-level descriptive statistics⁸

Variable	Number of observations	Mean	Standard deviation	Median	Minimum	Maximum
Scope1 GHG	634	384.54	1228.13	15.02	0.06	11,444.51
Total GHG	756	520.40	1438.00	45.66	0.36	11,444.51
Size (million \$)	846	119,500	327,944	30,978	2,293	2,573,126
Leverage	860	25.73	13.39	24.30	0.037	67.83

The bond issuer statistics show that the firms in the sample are large, with an average size of \$120 billion (total assets) and a median size of \$30 billion. However, there is considerable variation within the sample, with firms ranging from \$2.3 billion to \$2.6 trillion in total assets.⁹ Bond issuers in the sample are not highly leveraged, with an average and median leverage ratio of approximately 26%, and exhibit relatively small variations in leverage, with a standard deviation of 13%. As for carbon intensity, Scope1 emissions intensity shows

⁸ Those statistics are drawn from all firm-year observations available for all the companies in the sample between 2009 and 2015. Each firm-year observation is only accounted once, therefore the statistics do not allocate different weights on companies according to the number of bond they issued during the sampling period.

⁹ The mean of total assets is largely skewed upwards because of the big financial companies that have balance sheets with an order of magnitude of trillions of US\$.

considerable variation among companies, ranging from 0.06 to 11,445 tCO_{2eq} per million dollar of revenue. Average Scope 1 emissions intensity is 384.54 tCO_{2eq}/M, while the median is approximately 15.02 tCO_{2eq}/M and 75% of the issuers have an emissions intensity below 190 tCO_{2eq}/M. This skewedness is striking and reveals that, although the bulk of emissions intensities are in the tens of tCO_{2eq}/M, a few companies have substantially higher emissions intensity (see Table 5 for breakdown by sector and Figure 3 for a graphic illustration). Total GHG emissions intensity show similar patterns, with a higher average of 520 tCO_{2eq}/M and median of 45.66 tCO_{2eq}/M.

When comparing those descriptive statistics with those presented in Appendix 2 (Table 10), where companies are weighted according to the number of bonds they have issued over the time period, we can draw further conclusions on the companies that have issued more bonds in the time period. They are generally less carbon intensive, bigger in size – largely driven by the large number of bonds issued by the financial sector during this period of relatively low interest rates – and more leveraged.

Table 5, summarizes the sample distribution of key credit risk, company and bond level variables across industries.

Table 5: Descriptive statistics by industry

Industry	Number of bonds issued	Number of companies	Average Scope1 GHG (standard deviation - s.d.)	Average Spread (s.d.)	Average Rating (s.d.)	Average Rating (s.d.)	Average Amount (s.d.)
Communications	79	5	10.56 (8.05)	207.28 (223.83)	3.34 (0.92)	30,70 (8.85)	1,648.16 (2,114.99)
Consumer Discretionary	78	16	98.24 (259.15)	165.34 (143.61)	2.91 (0.93)	27,38 (16.84)	556.73 (371.46)
Consumer staples	116	16	39.02 (33.54)	89.15 (44.09)	4.06 (0.84)	33.75 (8.5)	680.18 (397.64)
Energy	24	11	329.78 (267.99)	139.98 (114.15)	3.33 (1.05)	17.84 (7.17)	908.33 (477.69)
Financials	393	20	13.16 (49.46)	130.51 (94.85)	3.57 (0.63)	22.22 (17.82)	1,173.63 (954.18)
Health Care	117	20	10.15 (8.76)	98.56 (49.98)	3.72 (0.94)	24.09 (9.49)	908.57 (764.63)
Industrials	44	12	318.62 (516.51)	108.44 (57.72)	3.75 (0.78)	28.14 (12.86)	959.16 (734.21)
Materials	57	12	578.60 (521.08)	100.65 (64.94)	3.93 (0.70)	26.25 (7.32)	598.02 (290.22)
Technology	142	21	7.09 (14.89)	120.93 (100.53)	4.09 (0.86)	18.64 (9.70)	1,097.12 (766.11)
Utilities	25	11	3,757.66 (3,043.56)	123.14 (116.74)	2.96 (0.68)	35.33 (5.29)	492 (246.09)
Total	1,075	144					

The majority of observations are in the Financial Services (37%), Technology (13%), Health Care (11%), and Consumer Staples (11%). The industries that issued the least bonds in the sample period are Utilities (25 bonds representing 2.3% of observations) and Energy (2.2% of observations).

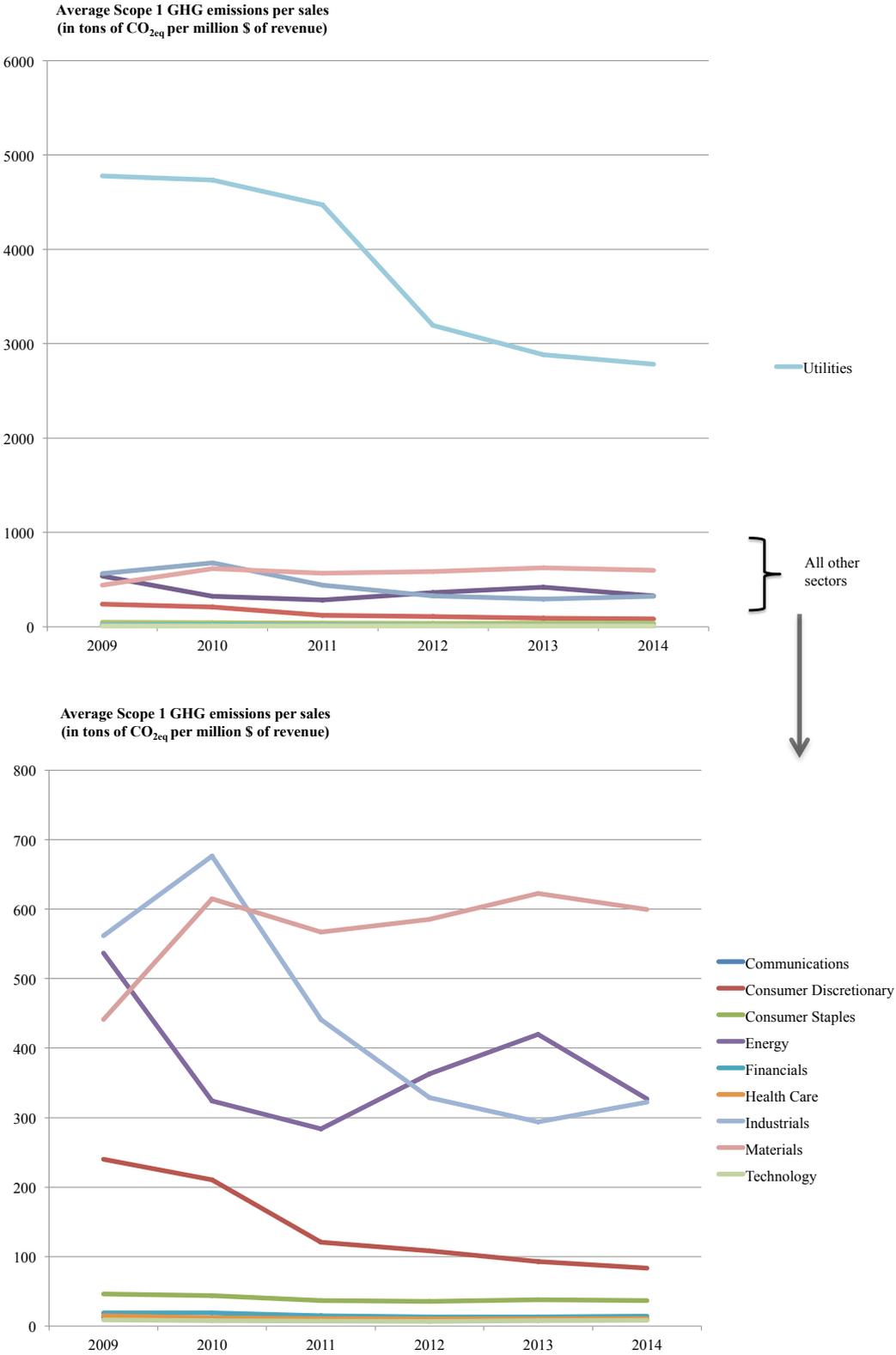
The utilities sector is comprised of 11 electric utilities, including Dominion Resources, Duke Energy, Entergy, Exelon Corp, Questar Corp, and The Southern Company. Bonds issued by utilities have the second lowest ratings after Consumer Discretionary, with an average of 2.96 (1 being the lowest and 6 the highest). Utilities exhibit an average credit spread of 123.14 basis points, ranking fifth highest industry out of ten after Communications, Consumer Discretionary, Energy and Financials. Surprisingly, although the utilities industry is the most

highly leveraged sector (35.33 ratio on average), utilities have issued the smallest bonds compared to all other sectors: \$492 million on average.

Figure 3 illustrates the evolution of Scope 1 emissions intensity by sector between 2009 and 2014 for the sample companies. As expected, utilities exhibit significantly higher carbon emissions intensity than all the other sectors. Although, utilities' emissions intensity has dropped drastically during this period – from almost 5,000 tCO_{2eq}/\$M to less than 3,000 tCO_{2eq}/\$M in 2014 – they were still five times more carbon intensive than the second most carbon-intensive sector, Materials.

Other highly carbon-intensive sectors include Energy, Industrials and Consumer Discretionary (including airline companies). The carbon intensity of Industrials and Consumer Discretionary is also trending downwards, while Materials' carbon intensity has increased and the Energy sector's carbon intensity exhibits wide fluctuations. As can be expected, the lowest carbon-intensive sectors (for direct emissions) are Consumer Staples, Financials, Health Care, Technology and Communications.

Figure 3: Average Scope 1 GHG emissions intensity of the sample companies per sector



4) Empirical methodology

Hypothesis 1

Bond yield modeling literature suggests that the most significant variables explaining variations of credit spread for new issues are: subordination status, company size, leverage, profitability (Graham and Maher, 2006), as well as bond maturity, interest coverage and capital intensity (Bauer and Hann, 2010). In addition, theory suggests that such financial variables may have incremental explanatory power beyond the information included in bond ratings for bond yields, exerting both direct and indirect influence on the pricing of bonds. Some empirical studies have confirmed this theory, and showed that financial variables have independent effects on bond yields (Ederington et al., 1987; Reiter and Ziebart, 1991; Ziebart and Reiter, 1992).

In the basic empirical model to test hypothesis 1, we therefore include GHG emissions intensity, interest rates, company-level financial variables that were shown to be a determinant of credit spread: leverage and size, as well as bond characteristics: bond rating, amount issued and maturity. Compared to the previous studies aforementioned a few differences in the model can be highlighted:

- Subordination status was not included because of lack of data. However, we do not expect that it would be correlated with carbon emissions intensity, so there is little risk that not including this variable would bias the results.
- Interest coverage¹⁰ was not included, because of the insufficient number of observations, reducing the sample to half. Moreover, we assume that the information on the capacity of the company to repay its debt is already captured by the leverage ratio.
- Bond rating is included in the model because we assume that it is a strong predictor of credit spread and can be correlated with carbon intensity, as explained in the conceptual framework (see II.3). We assume that carbon emissions intensity can have an impact on credit risk directly in the competitive bond markets, in addition to the indirect impact through credit rating.
- Profitability and capital intensity were not included in this empirical model.¹¹

¹⁰ Interest coverage defined as the earnings before taxes and interest divided by the interest expense is a measure of how easily a company can cover interest payments with its earnings; thus higher interest coverage indicates a lower credit risk.

¹¹ An additional test will be done before submitting to publication to estimate the correlation between profitability and capital intensity with carbon intensity respectively. If we find a strong correlation for either variable, it will be included in the model.

We derive the following empirical equation:

Equation 1:

$$Spread_i = \beta_0 + \beta_1 Scope1GHG_i + \beta_2 Interest_i + \beta_3 Size_i + \beta_4 Leverage_i + \beta_5 Rating_i + \beta_6 Amount_i + \beta_7 Maturity_i + u_i$$

This model is estimated with an Ordinary Least Squares (OLS) regression, using clustered standards errors at the company level. We use clustered standard errors to account for the fact that most companies issued several bonds over the time period, so there is a risk of autocorrelation of the error terms, which could result in exaggerated t-statistics. The model is estimated using industry and year fixed effects (for the third column in Table 6), because we believe that both credit spread and emissions intensity are correlated with sectors and years.

Hypothesis 2

The second hypothesis tests the evolution of the impact of GHG emissions intensity on credit spread over time. To equation 1, we add interaction terms between the independent variable of interest (*Scope1 GHG*) and year dummy variables. The left out category is the year 2010. Industry fixed effects are maintained in this estimation (although not reported in the following equation).

Equation 2:

$$Spread_i = \beta_0 + \beta_1 Scope1GHG_i + \beta_2 Interest_i + \beta_3 Size_i + \beta_4 Leverage_i + \beta_5 Rating_i + \beta_6 Amount_i + \beta_7 Maturity_i + \beta_8 Y2011_i + \beta_9 Y2012_i + \beta_{10} Y2013_i + \beta_{11} Y2014_i + \beta_{12} Scope1GHG*Y2011_i + \beta_{13} Scope1GHG*Y2012_i + \beta_{14} Scope1GHG*Y2013_i + \beta_{15} Scope1GHG* Y2014_i + \beta_{16} Scope1GHG* Y2015_i + u_i$$

Hypothesis 3

The third hypothesis tests the impact of carbon intensity on credit spread, for companies in the utilities sector as compared to all other sectors. We thus add one interaction variable between *Scope1GHG* and the utilities dummy variable. Year fixed effects are maintained in this estimation (although not reported in the following equation).

Equation 3:

$$\begin{aligned} \text{Spread}_i = & \beta_0 + \beta_1 \text{Scope1GHG}_i + \beta_2 \text{Interest}_i + \beta_3 \text{Size}_i + \beta_4 \text{Leverage}_i + \beta_5 \text{Rating}_i + \\ & \beta_6 \text{Amount}_i + \beta_7 \text{Maturity}_i + \beta_8 \text{Communications}_i + \beta_9 \text{Consumer Discretionary}_i + \\ & \beta_{10} \text{Consumer Staples}_i + \beta_{11} \text{Energy}_i + \beta_{12} \text{Financials}_i + \beta_{13} \text{Health Care}_i + \beta_{14} \text{Industrials}_i + \\ & \beta_{15} \text{Materials}_i + \beta_{16} \text{Utilities}_i + \beta_{17} \text{Scope1*Utilities} + u_i \end{aligned}$$

In the light of the existing literature presented in section III, my study is novel in several ways: in its scope, data, and methodology. It is the first study looking at the impact of carbon risk on bond yields in the primary bond market. Out of the two papers focusing on carbon risk, Chen and Gao studied carbon risk in the specific context of U.S. electric utilities but in the secondary bond market. Further, this study used older data (2002-2008) gathered before the mandatory reporting of GHG put in place by the U.S. EPA. Indeed, since 2010, the Greenhouse Gases Reporting Program requires mandatory GHG reporting from large sources – companies emitting 25,000 metric tons or more of CO_{2eq} per year (EPA, 2016). My sample contains data from 2009 through 2014, thus is more likely to have better GHG emissions data.¹² The second paper examining carbon risk looked at a very different market: bank loans in Australia (Jung et al., 2014), so my study is complementary. Finally, although my analysis focuses on the utilities sector, it uses a pool of data from the whole economy and then employs interaction terms to tease out the particular effects on the utilities sector to avoid the problems of small sample size, differentiating it from previous analyses drawing data from targeted sectors (Chen and Gao, 2012; Schneider, 2010).

¹² Gao and Chen, 2012 report that the scope of their for their analysis on the cost of debt was 35 companies, and their sample only contained 117 company-year observations.

V. Results and discussion

1) Regression results

a) Hypothesis 1

Table 6: OLS regression results with the credit spread as dependent variable

Dependent variable: Spread			
	(1)	(2)	(3)
Scope1 GHG		0.0011 (0.004)	-0.004 (0.004)
Interest	-1.684 (5.99)	0.669 (6.86)	-13.250 (9.96)
Size	-20.811*** (4.16)	-23.049*** (5.61)	-12.972** (5.43)
Leverage	0.764** (0.36)	0.923** (0.40)	0.701** (0.36)
Rating	-220.02*** (44.45)	-211.50*** (53.21)	-242.125*** (48.93)
Amount	30.348*** (3.42)	30.302*** (3.57)	27.882*** (2.28)
Maturity	1.862*** (0.22)	1.744*** (0.25)	1.662*** (0.28)
<i>Industry Fixed Effects</i>	Yes	Yes	Yes
<i>Year Fixed Effects</i>	No	No	Yes
Adjusted R ²	0.525	0.508	0.588
Number of observations	1,013	823	823

Note: robust standard errors are reported in parenthesis below the coefficients. The level of statistical significance is represented by stars as follows: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$.

Table 6 reports multivariate regressions results of the initial credit spread model developed to test Hypothesis 1. Column (1) reports the results of the basic model, which only comprises the control variables and industry fixed effects but not the independent variable of interest (*Scope1 GHG*). In Column (2), we present the findings of the model with *Scope1 GHG* (see **Equation 1**), estimated with industry fixed effects only, and in Column (3) the same model is estimated with industry and year fixed effects.¹³

¹³ As credit spreads are relative measures of bond yields compared to treasury yields on the day of issuance, and as 10 year treasury yields at the time of bond issuance are incorporated in the basic model, I assumed that a time dimension was already incorporated in the model, hence the first tests without year fixed effects.

The confidence in the model is supported by the adjusted R^2 ranging between 0.53 and 0.58. In addition, across the three model specifications, the control variables have fairly constant coefficients that are statistically significant at the 5% or 1% confidence level (except for *Interest*), with signs corresponding to what was expected (see Table 2). As expected, *Rating* has the biggest impact on credit spread, as doubling the bond rating reduces the average spread by 220 to 242 basis points, *ceteris paribus*¹⁴.

Adding *Scope1 GHG* reduces the number of observations to 823, but does not change the results structurally. To assess the economic significance of the findings, based on the average emissions intensity illustrated in Figure 3, we look at the impact of a change of 100 tCO₂eq/\$M on the credit spread. This represents a big change in carbon intensity for the lowest carbon-intensive sectors, but is reasonable when considering the carbon-intensive sectors of interest, which have average intensities in the order of magnitude of 100 or 1,000 tCO₂eq/\$M.

Column (2) results suggest that an increase in carbon intensity of 100 tCO₂eq/\$M increases on average the credit spread by 0.11 basis points (bp), but the coefficient is not statistically significant. Column (3) results suggest that, on the contrary, such increase in carbon intensity decreases on average the credit spread by 0.4 bp, although this result is not statistically significant either. 95% confidence intervals are [-0.7;0.9] and [-1.2;0.4] for columns (2) and (3) respectively. Given average spreads ranging from 98 to 207 bp according to industry, the confidence intervals suggest that the results are precise. Therefore, the results do not support Hypothesis 1 and indicate that, on average, there is no economically significant effect of carbon intensity on credit spread for new bond issues in this sample period.

The following tests will aim to assess whether there is a differential effect of credit spread in certain years according to the year of bond issuance or the industry. An F-test on the year fixed effects confirmed the joined significance of year dummies to explain credit spread, and as carbon intensity changed over time, the following models were run with both industry and year fixed effects.

¹⁴ All following results are interpreted *ceteris paribus*, or « all else being constant, but this will not be reported to avoid burdening the text.

Hypothesis 2

Table 7: OLS regression results with the credit spread as dependent variable and year interactions

Dependent variable: Spread	
Scope1 GHG	-0.003 (0.004)
Interest	-13.479 (10.06)
Size	-12.752** (5.48)
Leverage	0.684* (0.367)
Rating	-243.08*** (50.35)
Amount	27.916*** (2.27)
Maturity	1.690*** (0.27)
2011	-0.531 (13.02)
2012	-31.762* (17.38)
2013	-63.446*** (20.57)
2014	-95.603*** (20.72)
2015	-77.753*** (19.112)
Scope1 GHG x 2011	0.0004 (0.007)
Scope1 GHG x 2012	-0.0032 (0.0037)
Scope1 GHG x 2013	-0.0013 (-0.13)
Scope1 GHG x 2014	0.119** (0.05)
Scope1 GHG x 2015	0.015** (0.006)
<i>Industry Fixed Effects</i>	Yes
<i>Year Fixed Effects</i>	Yes
Adjusted R ²	0.591
Number of observations	823

Note: robust standard errors are reported in parenthesis below the coefficients. The level of statistical significance is represented by stars as follows: *** = p<0.01, ** = p<0.05, * = p<0.1.

Table 7 reports multivariate regressions results of the model developed in **Equation 2** to test Hypothesis 2. The coefficients and statistical significance of all the control variables are very similar to those in Column (3) of Table 6, which contributes to our confidence in the robustness of the model. For the year dummy variables, the left out year is 2010. The coefficients on the year dummy variables increase considerably year after year (except for 2015), and are almost all statistically significant at the 10% or 1% level. They are largely negative reflecting that credit spreads have decreased on average over the years since 2010, probably reflecting changing macroeconomic conditions, or an increase in the number of transactions in the U.S. bond market.

The coefficients on the year-carbon intensity interaction terms can be interpreted as the additional impacts of carbon intensity on credit spread in such year as compared to 2010. The coefficients on interaction terms show an interesting pattern: although there is no statistically significant additional effect of carbon intensity on credit spread in 2011, 2012, and 2013 as compared to 2010, there is a statistically significant additional effect in 2014 and 2015. The 95% confidence intervals on the interaction terms for years 2011 through 2013 confirm with precision that the coefficients are not different from zero.¹⁵

Adding up the coefficients on *Scope1 GHG* and the interaction term¹⁶, we conclude that, for bonds issued in 2014, an increase in carbon intensity by 100 tCO₂eq/\$M increases the spread by 11.6 basis points (bp). This result is statistically significant at the 5% confidence level. The precision of the estimate is not very high (with a 95% confidence interval of [1.72 ; 21.48]), but reflects a very small to moderate impact of carbon intensity on credit spread. Indeed, considering the utilities sector average credit spread of 123.14 bp, this represents a 1.3% to 17.4% relative increase in credit spread. For bonds issued in 2015, the impact is much smaller: a 1.3 increase in basis points for a 100 tCO₂eq/\$M increase in carbon intensity. This result is significant at the 10% level. The 95% confidence interval of [-0.007 ; 2.5] is precise and indicates a very small to non-existent economic impact.

¹⁵ Those confidence intervals are respectively: [-1.3 ; 1.3], [-1.05 ; 0.4] and [-2.2 ; 1.9] for years 2011, 2012 and 2013. They represent the additional impact of a 100 tCO₂eq/\$M increase in carbon intensity on credit spread in basis points as compared to 2010.

¹⁶ This is done with the STATA command “lincom” that gives the coefficient, statistical significance and 95% confidence interval of the linear combination of coefficients.

The results suggest a time trend and support hypothesis 2. Indeed, they reveal that the impact of carbon emissions on credit spread of new bond issues has increased over the sample period, from no impact in former years to a small-to-moderate impact in more recent years.

Hypothesis 3

Table 8 below reports multivariate regressions results of the model developed in **Equation 3** to test Hypothesis 3. The coefficients and statistical significance of all the control variables are again very similar to those in Column (3) of Table 6, which contributes to our confidence in the robustness of the model. The left out sector is Communications. The coefficients on the various Industries are all negative except for Financials, and only one is statistically significant (Consumer Staples).

Table 8: OLS regression results with the credit spread as dependent variable and utilities interactions

Dependent variable: Spread	
Scope1 GHG	-0.014 (0.024)
Interest	-13.341 (10.02)
Size	-13.044** (5.46)
Leverage	0.708* (0.37)
Rating	-242.885*** (49.76)
Amount	27.840*** (2.29)
Maturity	1.657*** (0.28)
Consumer Discretionary	-77.199 (53.49)
Consumer Staples	-64.385* (38.32)
Energy	-62.228 (42.16)
Financials	13.651 (38.48)
Health Care	-70.408 (42.87)
Industrials	-50.937 (39.51)
Materials	-36.814 (38.02)
Technology	-7.229 (38.57)
Utilities	-62.292 (51.61)
Scope1 GHG x Utilities	0.0106 (0.0236)
<i>Industry Fixed Effects</i>	Yes
<i>Year Fixed Effects</i>	Yes
Adjusted R ²	0.588
Number of observations	823

Note: robust standard errors are reported in parenthesis below the coefficients. The level of statistical significance is represented by stars as follows: *** = p<0.01, ** = p<0.05, * = p<0.1.

The coefficient on the interaction term between *Scope1GHG* and *Utilities* reflects the additional sensitivity of credit spread to carbon intensity for utilities as compared to all other sectors. The coefficient suggests that an increase in carbon intensity by 100 tCO₂eq/\$M, increases credit spread by an additional 1.06 bp for utilities as compared to all other sectors, but this coefficient is not statistically significant. The confidence interval ([-3.6 ; 5.7]) is not narrow enough however to let us conclude that there is no additional impact of carbon intensity on credit spread for utilities. Indeed, using the sample average credit spread as a reference point (127.03bp), the 95% confidence interval reveals that an increase of carbon intensity by 100 tCO₂eq/\$M would have an additional impact ranging from a 2.8% decrease in credit spread to a 4.5% increase for utilities as compared to the impact on all other sectors. This is inconclusive and does not allow to either reject or validate Hypothesis 3.

Robustness checks

We carried out several tests to evaluate the robustness of the model and the results. First, an alternative common measure of financial leverage was used: Total Debt to Common Equity. Then, for the dependent variable of interest, total greenhouse gas intensity was used (Total GHG). This variable is a measure of Scope 1 and Scope 2 emissions scaled by the company's revenue (see Table 2), and thus reflects in addition companies' indirect emissions from energy consumption. Finally, an alternative method to match company level data to bond data was used. The fiscal year end month was ignored (and assumed to be December for all companies) and emissions data from the year previous to the bond issue were systematically used. This assumes that contrary to financial data, information on carbon emissions are not available to rating agencies or underwriters before the end of the fiscal year.

The results are highly robust to those three modifications, both in terms of overall significance (R^2), and in terms of sign, magnitude and level of statistical significance of the coefficients (except for interest rate, which sign has shown volatility in the previous models as well although it was never statistically significant).¹⁷

¹⁷ Regression results are available upon request.

2) Discussion

It is important to note that across all model specifications containing GHG emissions variables, the number of observations never exceeds 930, which may explain the poor precision of some of our estimates.

The results obtained invalidate the first hypothesis that carbon intensity has an average positive impact on credit spread in the primary bond market over our sample period. This differs from most of the results found in the literature looking at bond yields, both the studies looking at the impact of environmental concerns on credit spread in the primary bond market (Graham and Maher, 2006; Bauer and Hann, 2010) and those looking at the impact of carbon emissions on bond yields in the secondary market (Chen and Gao, 2012). A few hypotheses can be offered to explain those differences. First, the construction of the model itself may explain such results. Indeed, by including the rating in the credit spread, the results reflect estimations of the average impact of carbon intensity on credit spread, while bond rating is held constant. As explained in the conceptual framework we expect bond rating to be a channel through which carbon risk impacts credit spread. Thus the results may suggest that bond rating incorporates most of the explanatory power of carbon intensity, leaving little predictive power when credit rating is held constant. Those are the findings of Graham and Maher who conclude that environmental liabilities do not contain incremental information beyond bond rating in a model of bond yields in the presence of a firm's bond rating (Graham and Maher, 2006). Second, the model might still contain omitted variable bias. Indeed, the model does not include any information relative to the actions taken by carbon-intensive companies to address their carbon risk. Such actions can go from acknowledging carbon risk and running scenarios of the impact of a 2°C world on the company's financial health and business model, to investing in technologies like Carbon Capture and Storage (CCS) for highly carbon-intensive power plants. Indeed, as found by Bauer and Hann, although environmental concerns are associated with a higher cost of debt financing, proactive environmental practices decrease the cost of debt (Bauer and Hann, 2010).

As highlighted by Menz in his study of the incorporation of CSR information in the European bond market, an alternative explanation could be that there is a difference between bond market theory and practice. This would suggest inefficiency in the U.S. corporate bond primary market, where all available information is not fully integrated into yields at issue (Menz, 2010).

The next set of results, however, validate our second hypothesis and suggest a time trend, whereby carbon intensity had no impact on credit spread until 2014, but does since then. These results are coherent as climate change has really been an increasing concern in the financial sphere in recent years. Bauer and Hann already found an increase over time in the relevance of environmental concerns for credit risk in the primary bond market in the United States, over the 1995- 2006 period (Bauer and Hann, 2010). However, our results are not consistent with the findings by Chen and Gao that carbon emission rates already had a positive impact on the cost of debt in the secondary bond market for electric utilities in the United States over the 2002-2008 period.

Our results do not allow for any conclusion as regards to the third hypothesis that carbon risk has a higher impact on credit spread for utilities than for other sectors. The dataset contains only 25 observations for utilities out of 1,075 bonds, which may drive the precision of the estimate downwards. In addition, from a macro perspective, the U.S. gas boom can offer a relatively low-cost carbon mitigation strategy for electric utilities. Thus one hypothesis could be that financial markets may not be as wary as one could expect of carbon intensity in the utilities sector in the United States, as compared to other places where mitigation options are more expensive (and include CCS for instance). This hypothesis is however not consistent with Chen and Gao's empirical results (Chen and Gao, 2012).

3) Implications

The results of this study have important implications for issuing companies. One of the core principles of corporate finance is to maximize shareholder value, which can be achieved by maximizing the value of future cash flows, and/or by minimizing the cost of capital, driven in part by the cost of debt. Although no significant results were found over the entire sample period, the analysis revealed annual trends suggesting that in recent years carbon risk has had a positive impact on credit risk for new bond issues, which could incentivize companies to pursue mitigation efforts.

The above results also have implications for institutional investors active in the corporate bond sector, in particular insurance companies and pension funds. If the corporate bond market is inefficient at incorporating information on carbon risk in bond yields, this can have substantial implications for those two categories of asset owners. Pension funds are highly risk averse in their investment strategies, since they act as fiduciaries on behalf of their

beneficiaries. As long-term investors, a growing number of pension funds is voicing its concerns about the impact of climate risks on their portfolios (Scott, 2014), hence the importance of market incorporation of information regarding carbon risks. Insurance and reinsurance companies, have relatively low investment risk profiles as well, due to capital requirements enforced by regulators to ensure the adequacy of their investment returns with their obligations (liabilities in the form of insurance policy). Climate change threatens the re/insurance sector's very business model with increased extreme weather events, changing mortality patterns, and the global transition to a low-carbon economy, potentially impacting both sides of a company's balance sheet (Brauner, 2002; McHale, 2012). The appropriate incorporation of carbon risk into corporate bond credit risk analysis is thus crucial to ensuring that the sector has the information it needs to make sound and prudent investment decisions.

VI. Conclusion

This paper investigates whether carbon risk is incorporated in corporate bond credit risk of new bond issues in the United States, with a particular focus on the utilities sector, which is the most carbon-intensive industry in the country. The fundamental hypothesis underlying the analysis is that carbon risk can affect the solvency of carbon-intensive borrowers by exposing them to costly legal and regulatory risks. To test those assumptions, we used carbon intensity as a proxy for carbon risk, and examined its impact on corporate bond yield spreads through empirical econometrics analysis. The results found no average impact of carbon risk on credit spread for new bond issues over the whole sample period, which is inconsistent with most of the results found in the related literature. A deeper analysis of heterogeneous effects over time, however, revealed that although carbon risk did not impact credit spread in the early years of this study (2010 through 2013), it had a small-to-moderate impact in 2014 (which is both economically and statistically significant) and a non-existent-to-small impact in 2015 (which is statistically but not economically significant). The dataset did not permit to get any conclusive results on the differential impact of carbon risk on credit spread for the utilities sector. These findings reveal how carbon risk is currently perceived and accounted for by financial actors, providing information useful to issuing companies and institutional investors regarding the efficiency of corporate bond markets. Our conceptual framework suggests that carbon risk can impact credit spread both directly in the competitive bond market and indirectly through bond rating. As this study included bond ratings in the empirical models, our results reflect the incremental impact of carbon risk on credit spread, beyond the potential

impact through bond rating. Future research should thus be directed towards investing the indirect impact channel by studying the impact of carbon risk on credit rating. Additional analysis could be done to determine whether the time trend continues in 2015 and beyond, given the strong signal sent to financial markets by the outcome of COP21 and the Paris climate agreement. Finally, the European bond market could also be interesting to study, as Europe's more expensive climate mitigation options may have a more profound effect on how carbon risk is perceived by financial actors.

Acknowledgments

I would like to thank Professor Kelly Sims Gallagher for welcoming me in her research group and providing me with fantastic guidance and inspiration, Professor Patrick Schena for his outstanding support and enthusiasm, Professor Julie Schaffner for her precious help in Econometrics, and Laura Kuhl for her extremely helpful comments. I would also like to thank Min Soo Kim and Kelsey Smithwood for taking the time to review my work. Finally, I would like to give special thanks to Thibaut Perol for his help in constructing my dataset and his precious daily support.

Appendix

Appendix 1

Table 9: Recoding credit rating classifications

Moody's Rating	S&P Rating	Fitch Rating	Assigned Rating Code	Rating grade ¹⁸
Aaa	AAA	AAA	6	Investment Grade
Aa1	AA+	AA+	5	
Aa2	AA	AA		
Aa3	AA-	AA-		
A1	A+	A+	4	
A2	A	A		
A3	A-	A-		
Baa1	BBB+	BBB+	3	
Baa2	BBB	BBB		
Baa3	BBB-	BBB-		
Ba1	BB+	BB+	2	Non-Investment Grade
Ba2	BB	BB		
Ba3	BB-	BB-		
B1	B+	B+	1	
B2	B	B		
B3	B-	B-		

¹⁸ An investment grade is a rating that indicates that a municipal or corporate bond has a relatively low risk of default.

Appendix 2

Table 10: Issuer-level descriptive statistics weighing the number of bonds issued over the time period

Variable	Number of observations	Mean	Standard deviation	Median	Minimum	Maximum
Scope1 GHG	849	131.90	780.72	2.46	0.06	11,444.51
Total GHG	954	225.57	951.93	20.95	0.36	11,444.51
Size (million \$)	1,039	534,01	771,401	102,908	2,512.54	2,573,126
Leverage	1,029	30.06	14.33	29.48	1.18	63.03

References

American Electric Power Co v. Connecticut, 2010

Supreme Court of the United States. *American Electric Power Co., Inc. et Al., v. Connecticut et Al.*, 2010.

Bauer and Hann, 2010

Rob Bauer, and Daniel Hann. “Corporate Environmental Management and Credit Risk - Working Paper,” June 30, 2010.

Brauner, 2002

Christian Brauner. “Opportunities and Risks of Climate Change.” Swiss Reinsurance Company, 2002.

Brigham and Ehrhardt, 2011

Accounting: Commitment or Propaganda (2006): 111–42. Brigham, Eugene F., and Michael C. Ehrhardt. *Financial Management: Theory and Practice*. 13th ed. Mason, OH: South-Western Cengage Learning, 2011.

C2ES, 2016

Center for Climate and Energy Solutions, C2ES. “California Cap and Trade.” Accessed January 21, 2016. Available from: <http://www.c2es.org/us-states-regions/key-legislation/california-cap-trade#Details>.

Carney, 2015

Carney, Mark. “Breaking the Tragedy of the Horizon—climate Change and Financial Stability.” *Speech given at Lloyd’s of London by the Governor of the Bank of England* 29 (2015). Available from: http://www.bjmgerrard.nl/wp-content/uploads/2015/09/Speech-given-by-Mark-Carney_climate-and-financial-crises_29sept2015.pdf.

CAT, 2015

Climate Action Tracker. “USA,” September 2015. Available from: <http://climateactiontracker.org/countries/usa.html>.

CDP, 2016

Carbon Disclosure Project. “What We Do - Investors.” Accessed April 10, 2016. Available from: <https://www.cdp.net/en-US/WhatWeDo/Pages/investors.aspx>.

Chava, 2011

Sudheer Chava. “Environmental Externalities and Cost of Capital,” (College of Management Georgia Institute of Technology, 2011).

Chen and Gao, 2012

Chen, Linda H., and Lucia Silva Gao. “The Pricing of Climate Risk.” *Journal of Financial and Economic Practice, Vol12 (2), Spring, 2012*, 115–31.

Chenet and Dupré, 2013

Hugues Chenet, and Stan Dupré. “Landscaping Carbon Risk for Financial Intermediaries.” 2° Investing Initiative, November 2013.

CII, 2009

Chartered Insurance Institute. “Coping with Climate Change - Risks and Opportunities for Insurers,” May 1, 2009.

Citibank, 2013

Citibank. “Rising Rates and the Effects on Spreads,” March 2013.

Clark et al., 2015

Gordon Clark, Andras Feiner, and Michael Viehs.

“From the stockholder to the stakeholder - How sustainability can drive financial performance” University of Oxford, Arabesque Partners, March 2015.

CTI, 2011

Carbon Tracker Initiative. “Unburnable Carbon – Are the World’s Financial Markets Carrying a Carbon Bubble?,” 2011.

CTI, 2013

Carbon Tracker Initiative. “Unburnable Carbon 2013: Wasted Capital and Stranded Assets,” 2013.

Deutsche Bank, 2012

Deutsche Bank Climate Change Advisors. “Sustainable Investing - Establishing Long-Term Value and Performance,” June 2012.

Ederington et al., 1987

Ederington, L. H., Yawitz, J. B., & Roberts, B. E. (1987). The information content of bond ratings. *Journal of Financial Research*, 10, 211-226.

EIA, 2016

U.S. Energy Information Administration (EIA). “What Is U.S. Electricity Generation by Energy Source?,” April 1, 2016. Available from: <https://www.eia.gov/tools/faqs/faq.cfm?id=427&t=3>.

EPA, 2015

US EPA, Climate Change Division. “U.S. Greenhouse Gas Inventory Report.” Reports & Assessments, December 12, 2015.

Available from: <http://www3.epa.gov/climatechange/ghgemissions/usinventoryreport.html>.

EPA, 2016

US EPA, OAR. “Greenhouse Gas Reporting Program (GHGRP).” Policies and Guidance, February 4, 2016. <http://www.epa.gov/ghgreporting>.

Feinland Katz, 2008

Laura Feinland Katz, Standard and Poor’s. “Rating Agencies and Their Methodologies.”

presented at the Seminar, Senior Bank Supervisors from Emerging Economies, World Bank/IMF/Federal Reserve System, Washington DC, October 21, 2008.

Geiling, 2015

Geiling, Natasha. “Why These Tiny Island Nations Are Planning To Sue Fossil Fuel Companies.” *ThinkProgress*, June 10, 2015.

Available from: <http://thinkprogress.org/climate/2015/06/10/3667580/south-pacific-climate-change-lawsuit/>.

Graham and Maher, 2006

Allan Graham, and John J. Maher. “Environmental Liabilities, Bond Ratings and Bond Yields.” *Advances in Environmental Accounting and Management* Volume 3 - Environmental

IPCC, 2014

Pachauri, Rajendra K., M. R. Allen, V. R. Barros, J. Broome, W. Cramer, R. Christ, J. A. Church, et al. “Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change,” 2014. Available from: <http://epic.awi.de/37530/>.

Jung et. al, 2014

Jung, Juhyun, Kathleen Herbohn, and Peter Clarkson. “The Impact of a Firm’s Carbon Risk Profile on the Cost of Debt Capital: Evidence from Australian Firms,” 2014. Available from: https://www.uts.edu.au/sites/default/files/Peter%20Clarkson_22.09.14.pdf.

Kivalina v. ExxonMobil, 2011

Native Village of Kivalina v. ExxonMobil - Appeal from the United States District Court for the Northern District of California, 2011.

Labatt and White, 2007

Labatt, Sonia, and Rodney R. White. *Carbon Finance: The Financial Implications of Climate Change*. Wiley Finance. Hoboken, N.J: John Wiley & Sons, 2007.

McHale, 2012

Cynthia McHale, and Sharlene Leurig. “Stormy Future for U.S. Property /Casualty Insurers: The Growing Costs and Risks of Extreme Weather Events.” *Ceres*, September 2012. Available from: <http://content.healthaffairs.org/content/22/3/61.short>.

Menz, 2010

Klaus Michael Menz. “Corporate Social Responsibility: Is It Rewarded by the Corporate Bond Market? A Critical Note,” September 2010.

Moody’s, 2015

Moody’s Investors Service. “Paris Agreement Advances Adoption of Carbon Regulations; Credit Impact to Rise,” December 14, 2015.

MSCI, 2015

MSCI. “Beyond Divestment: Using Low-Carbon Indexes,” April 2015.

PDC, 2016

“Portfolio Decarbonization Coalition Now Overseeing Decarbonization of \$600bn Assets Under Management « The Portfolio Decarbonization Coalition.” Accessed January 22, 2016. Available from: <http://unepfi.org/pdc/portfolio-decarbonization-coalition-overseeing-decarbonization-of-600bn-assets-under-management/>.

PWC, 2010

PricewaterhouseCoopers. (2010). Green products: Using sustainable attributes to drive growth and value: Sustainable business solutions. Available at: <http://www.pwc.com/us/en/corporate-sustainability-climate-change/assets/green-products-paper.pdf>.

Reiter and Ziebart, 1991

Reiter S.A., & Ziebart, D. A. (1991). Bond yields, ratings and financial information: Evidence from public utility issues. *The Financial Review*, 26(February), 45-73.

RGGI, 2016

“Regional Greenhouse Gas Initiative (RGGI) CO2 Budget Trading Program - Program Overview.” Accessed January 21, 2016. Available from: <http://www.rggi.org/design/overview>.

Ross et al., 2007

Ross, Christina, Evan Mills, and Sean B. Hecht. “Limiting Liability in the Greenhouse: Insurance Risk-Management Strategies in the Context of Global Climate Change.” *Stanford Environmental Law Journal* 26 (2007): 251.

S&P, 2015

Standard and Poor’s Ratings Services. “How Environmental And Climate Risks Factor Into Global Corporate Ratings,” October 21, 2015.

Schneider, 2010

Thomas E. Schneider. “Is Environmental Performance a Determinant of Bond Pricing? Evidence from the U.S. Pulp and Paper and Chemical Industries.,” July 12, 2010.

Scott, 2014

Mike Scott. “Pension Funds Face New Era of Disclosure On Climate Risks.” *Forbes*, February 3, 2014. <http://www.forbes.com/sites/mikescott/2014/02/03/pension-funds-face-new-era-of-disclosure-on-climate-risks/>.

Sharfman and Fernando, 2007

Sharfman, Mark P., and Chitru S. Fernando. “Environmental Risk Management and the Cost of Capital.” *Strategic Management Journal* 29, no. 6 (2008): 569–92.

SIFMA, 2013

The Securities Industry and Financial Markets Association. “The Role of Bonds in America,” 2013. Available from: <http://www.investinginbonds.com/learnmore.asp?catid=3&id=50>.

Stohr and Dlouhy, 2016

Greg Stohr, and Jennifer A Dlouhy. “Obama’s Clean-Power Plan Put on Hold by U.S. Supreme Court.” *Bloomberg.com*, February 9, 2016.

Available from: <http://www.bloomberg.com/politics/articles/2016-02-09/obama-s-clean-power-plan-put-on-hold-by-u-s-supreme-court>.

Tang and Yan, 2010

Tang, Dragon Yongjun, and Hong Yan. “Market Conditions, Default Risk and Credit Spreads.” *Journal of Banking & Finance* 34, no. 4 (April 2010): 743–53. doi:10.1016/j.jbankfin.2009.05.018.

Trusted Sources, 2011

Trusted Sources Research and Networks. “Insurance Companies and Pension Funds as Institutional Investors: Global Investment Patterns.” City of London, November 2011.

UNFCCC, 2015

UNFCCC. “Adoption of the Paris Agreement,” December 12, 2015.

U.S. Department of treasury, 2016

U.S. Department of the Treasury. “Daily Treasury Yield Curve Rates.” Accessed January 21, 2016. Available from: <https://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=yieldYear&year=2014>.

Zegart, 2014

Dan Zegart. “Want to Stop Climate Change? Take the Fossil Fuel Industry to Court | The Nation,” April 21, 2014. Available from: <http://www.thenation.com/article/179459/want-stop-climate-change-take-fossil-fuel-industry-court#>.

Ziebart and Reiter, 1992

Ziebart, D. A., & Reiter S.A. (1992). Bond ratings, bond yields and financial information. *Contemporary Accounting Research*, 9, 252-282.