STAFF REPORTS

NO. 1014
APRIL 2022

REVISED
JANUARY 2024

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FEDERAL RESERVE BANK of NEW YORK

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Federal Reserve Bank of New York Staff Reports, no. 1014
April 2022; revised January 2024
JEL classification: G38, G24, G00

Abstract

Investor and policymaker concerns about climate risks suggest these risks should affect the risk assessment and pricing of corporate securities, particularly for firms facing stricter regulatory enforcement. Using corporate bonds, the authors find support for this hypothesis. Employing a shock to expected climate regulations, they show climate regulatory risks causally affect bond credit ratings and spreads. A structural credit model indicates that the increased spreads for high carbon issuers, especially those located in stricter regulatory environments, are driven by changes in firms' asset volatilities rather than asset values, highlighting that regulatory uncertainty affects security pricing. The results have important implications for policy-making.

Key words: climate risk, regulatory risk, fixed income

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1. Introduction

Investors and policymakers have become more concerned about the environmental and climate risks embedded in investor portfolios.[1] Of the three primary components of climate risk (physical, technological and regulatory), regulatory risk is the one that investors, policymakers, and others in the finance community believe has the most immediate relevance (Krüger, Sautner, and Starks, 2020; Stroebel and Wurgler, 2021), particularly because environmental regulatory costs can significantly affect firms' operating costs and cash flows (Karpoff, Lott, and Wehrly, 2005; Meng, 2017). Moreover, uncertainty about future regulation itself poses costs to firms and their investors (Pindyck, 1993; Brogaard and Detzel, 2015).[2] In fact, even if a country is not currently issuing new climate change legislation, regulatory risks can still get embedded in firms' cost of capital through the channel of regulatory uncertainty.

Researchers have begun to examine the effects of climate and environmental risk, particularly climate regulatory risk, on asset prices, but this work has focused primarily on equity prices.[3] In this paper we argue that analyzing corporate bonds can provide valuable insights into climate regulatory risk and its effects on firms' securities more generally. This approach is important for several reasons. Regulatory risk entails added uncertainty to both a firm's equity and debt, but as pointed out by Campbell and Taksler (2003), volatility can have opposite effects on stock and bond prices. In particular, volatility can increase the optionality of a company's equity, adding value to the stock price. At the same time it can increase the probability of default for the company's bonds (that is, it can entail more downside risk), thus, lowering the bond price. These relationships imply increases in climate regulatory risk can have mixed effects on equity prices, but more straightforward effects on bond prices. Thus, while much of the previous literature focuses on the effects of increased climate regulatory risks on equity prices, it is important to understand the effects on debt instruments as they may be even greater due to the downside risk inherent in such

[1] See, for example, Shultz (2017), Smith (2021), Jourde and Kone (2023), and Maloney (2023).

[2] In theoretical models such as Pastor and Veronesi (2013), political uncertainty regarding climate regulations affects asset prices. Empirically, Kaviani, Kryzanowski, Maleki, and Savor (2020) find a strong relationship between policy uncertainty and corporate credit spreads when they employ the Baker, Bloom, and Davis (2016) economic policy uncertainty index. Further, Brogaard and Detzel (2015) conclude that government economic policy related to regulation can have market-wide effects that are largely non-diversifiable and further, that policymakers can increase risk through "generating an environment of uncertainty about their future economic policy decisions."

[3] For recent climate risk research on equity prices, see, for example, Monasterolo and de Angelis (2020), Bolton and Kacperczyk (2021), Mukanjari and Sterner (2018), Ramelli et al. (2021), and Zerbib (2019). For recent climate risk research on other security prices, see for example, Pastor et al. (2022), and Goldsmith-Pinkham et al. (2023).

securities. Moreover, as pointed out by Gourio (2013), for many corporations, the bond market, rather than the equity market, is the marginal source of finance.

In considering the effects of regulatory risks on corporate bond ratings and pricing, we also examine whether the effects are compounded when firms' operations are located in states with more stringent regulatory enforcement. In the United States, significant environmental legislation exists at the federal level with rule making by the EPA. However, state governments generally hold the primary responsibility for enforcing these laws, and the states vary widely in their enforcement practices. Further, some states impose additional environmental restrictions beyond those required by the EPA.[4] We estimate regulatory risk exposure through aggregating measures of the regulatory stringency a firm faces depending on the geographical locations of the firm's establishments. Thus, even when two firms have objectively similar levels of environmental impact, depending on the local regulatory conditions of their facility locations, the regulatory risks they face can differ.

To sharpen identification, we employ an exogenous shock to firms' regulatory risk as a setting in which changes in climate regulatory risks can affect the pricing of firms' bonds and equities. Not only do we observe a sharp increase in the bond yield spreads of firms with high carbon footprints, we are able to use a structural credit model to quantify how much of the changes in yield spreads can be attributed to changes in asset value and asset volatility. Our analysis suggests that an increase in asset volatility is disproportionately more responsible for the observed pricing patterns, which is consistent with Campbell and Taksler (2003)'s suggestion that bond pricing is more vulnerable to volatility increases. The result is also reflective of the arguments in Stiglitz et al. (2017) and Berg et al. (2023) that uncertainty in climate change regulations has harmful effects on financial markets.

Testing our hypotheses requires measuring firms' environmental profiles, which we conduct through two primary methods. First, we employ an assessment of the firm's environmental quality by a third-party environmental, social and governance (ESG) rating agency (Sustainalytics). Second, we construct multiple measures of firms' carbon footprints using data from CDP (formerly known as the Carbon Disclosure Project).

[4]Prior studies have documented uneven enforcement across states (e.g. Konisky, 2007; Mattera and Baggaley, 2021; Gulen and Myers, 2021). As Mattera and Baggaley (2021) put it, *"Frequently overlooked is the fact that the country's enforcement system is actually divided between the EPA and the states. This shared responsibility, which in the academic literature is known as environmental federalism.* They also point out that this shared responsibility is *"a source of tension between levels of government."*

In initial analyses, we examine whether bond credit ratings and yield spreads are associated with firms' environmental profiles, the regulatory risk exposures of their facilities, and the interaction between the two. Employing a sample of newly-issued corporate bonds, we document important empirical relationships. First, we find that firms' environmental profiles, whether measured by a third-party rating or through the firms' carbon footprints, are unconditionally reflected in bond credit ratings and yield spreads. Firms with lower environmental scores, higher levels of carbon emissions, or higher carbon intensities (carbon emissions scaled by firm revenue) exhibit lower credit ratings and higher yield spreads, on average. These findings echo previous results in the equity market that carbon risk is priced into average stock returns and the tail risk of stocks (Bolton and Kacperczyk, 2021, 2022; Ilhan, Sautner, and Vilkov, 2021). Second, and more importantly, there exists a statistically and economically significant interaction effect on credit ratings and spreads between a firm's environmental profile and its regulatory environment. The differences in credit ratings and yield spreads for low environmental score firms and high-emission firms are more pronounced if the firms operate in states where environmental regulations are enforced more stringently. This result suggests that regulatory risk is an important channel through which firms' environmental profiles affect their credit risks.

Recognizing the potential endogenous relationship between firms' environmental profiles and market participants' perceptions of the firms' risks, we consider a setting in which expectations regarding future climate regulations receive an exogenous shock, namely the December 2015 Paris Agreement, under which world governments pledged to take actions to limit future global temperature increases. When the Agreement was announced, a natural implication for rating agencies and bond investors to draw was that governments—including U.S. federal and state governments—would tighten their environmental regulations related to the mitigation of climate change.[5] In fact, consistent with this presumption, at least one rating agency adjusted their baseline scenarios to include expectations of increased regulations after the Paris Agreement (Moody's, 2016). Survey results also suggest that firms upwardly revised their beliefs about future regulation intensity in their disclosure to the CDP around the time of the Agreement (Ramadorai and Zeni, 2021).

[5]The fact that so many nations would sign on to the Paris Agreement does not appear to have been foreseen far in advance of the United Nations Climate Change Conference, which began on November 30, 2015. For example, a headline in a British newspaper on November 1, 2015 stated "Why climate treaty will be the flop of the year." In mid-November there still existed divisions among the world's leading countries regarding a deal. As late as November 23, the EU's climate and energy czar warned that an agreement was far from certain.

This shock implies that firms would face greater climate regulatory risk, especially those firms more exposed to this risk because of their business activities. The importance of this event is reflected in the fact that it is the third highest spike in the Engle, Giglio, Kelly, Lee, and Stroebel (2020) climate change news index, which the authors constructed over the 1984 to 2017 period to capture innovations in climate change information.[6]

To test the hypothesis that the Paris Agreement had greater effects on U.S. corporate bonds that are more exposed to climate regulatory risks, we employ difference-in-differences analyses of firms' credit ratings and yield spreads in the months around the Agreement. The treated bonds are those issued by firms that have poor environmental scores, high carbon emissions, high carbon intensities prior to the Agreement, or that belong to a top 15 carbon-emitting industry. Using bonds traded during the testing period, we find that after the Agreement, bonds from the treated firms experience an average decrease in credit ratings of 0.48 to 0.63 notch relative to bonds from other firms. These results support the hypothesis that changes in climate regulatory risk affect bond credit ratings for firms with more significant carbon footprints. Further, the results corroborate the anecdotal evidence that credit rating analysts consider expected regulatory changes when evaluating climate risk effects on firms' default risks. In addition, we find that the yield spreads of treated bonds increase significantly after the Paris Agreement, suggesting that beyond the credit rating analysts, bond investors also react to potential regulatory changes. For example, yield spreads increased by about 35 bps for bonds issued by firms belonging to the top carbon-emitting industries. Similarly, bonds issued by firms with high total carbon emissions, high carbon intensity, or a low environmental score also experience a significant increase in yield spreads after the Paris Agreement.

Given that the expected tightening of environmental regulations following the Paris Agreement would presumably be carried out under the state-enforcement regime that currently exists, we hypothesize that any effects on credit ratings and yield spreads should be stronger for issuers operating in high-enforcement states. Consequently, we conduct a triple-difference analysis in which we include an indicator variable for firms operating in states with relatively more enforcement actions. The analysis result indicates that, following the Paris Agreement, the changes in credit ratings and yield spreads for environmentally problematic firms are more pronounced if a firm's establishment locations are in states with stricter enforcement of environmental regulations.

[6]See Engle, Giglio, Kelly, Lee, and Stroebel (2020), Figure 2, p. 1193.

While existing literature provides evidence that the value of equities also dropped for carbon-intensive firms after the Paris Agreement, we note that the drop in equities as found, for example, in Monasterolo and de Angelis (2020) and Mukanjari and Sterner (2018) seems small relative to the yield spread changes we observe for corporate bonds. To jointly examine the change in equity markets with the change in bond markets, we use a structural model based on the Merton (1974) credit model to study the drivers of the observed credit spread changes for high-carbon issuers.[7] Indeed, the analysis shows that under the assumption of constant volatility, the surge in credit spreads is too large based on the sensitivity of bond yields to changes in equity value (Schaefer and Strebulaev, 2008). In other words, the underlying structural parameters must have changed around the Paris Agreement to account for the change in both equity value and credit spreads. We hence estimate the asset value and asset volatility for bond issuers both before and after the announcement of the Paris Agreement. Our results reveal a modest drop in asset value and a significant increase in asset volatility for the high carbon firms relative to the control firms. While the high carbon firms' drop in asset value quickly reverses within a few months after the Paris Agreement, the increase in asset volatility remains persistent.

Based on the structural credit model, we calculate the default probabilities for the treated and control firms and observe a significant increase in the treated firms' default probabilities of around 2.3 percentage points shortly after the Paris Agreement. The counterfactual analysis suggests that the increase in asset volatility contributes more to this change in default probability than the change in asset value. This result is consistent with the evidence in Goldsmith-Pinkham et al. (2023) that suggests uncertainty rather than a change in asset value is the primary driver of changes in municipal bond yields due to physical climate change risk (i.e., sea-level rise exposure). Our analyses demonstrate that climate regulatory risks can raise the probabilities that corporate bond issuers default, underscoring their potential role in generating systemic risks. Furthermore, given that critical financial institutions hold corporate bond securities on their balance sheets (Boyarchenko et al. (2021); Papoutsi et al. (2022), the results imply that climate regulatory risks can adversely affect these institutions.

The bond pricing results suggest that after the Paris Agreement event some investors would

[7] Goldsmith-Pinkham et al. (2023) provide guidance by having adapted the Merton model to examine municipal bond credit rating changes related to sea level rise.

have reevaluated their holdings in bonds more exposed to climate risk. Substantial theoretical and empirical evidence provides evidence that various segments of the institutional investor population employ differing investment strategies regarding ESG risks, including climate risks.[8] Consequently, we hypothesize that after the Paris Agreement reactions should differ between the two major institutional investor types in the corporate bond market, mutual funds and insurance companies, primarily due to the variations in their typical investment horizons (Massa et al., 2013). Using difference-in-differences analyses, we find after the Paris Agreement, insurance companies, which tend to have longer investment horizons, lowered their holdings in the treated bonds. Mutual funds, which tend to have shorter investment horizons, either kept the same amount or increased their holdings, depending on the definition of firms' problematic environmental profiles.

Our analyses and results contribute on a number of dimensions. First, we contribute to the literature on the pricing of firm securities with respect to climate and environmental risks and news about those risks.[9] Our evidence that corporate bond investors demand returns from issuers with poor environmental performance is consistent with earlier work on bank loans (Chava, 2014), municipal bonds (Painter, 2020; Goldsmith-Pinkham et al., 2023), and equities (Bolton and Kacperczyk, 2021, 2022). Previous work on environmental news has focused primarily on the stock market response (e.g., Krüger (2015), Karpoff, Lott, and Wehrly (2005), Murfin and Spiegel (2020), and Ramelli et al. (2021)), although some work has considered effects to fixed income instruments such as bank loans (e.g., Ivanov, Kruttli, and Watugala (2023)). Our analysis considers not only how credit rating analysts and bond investors respond to changes in perceptions of firms' environmental regulatory risks, but also whether the responses affect firms' asset values or asset volatilities. In addition, through our examination of firm facility locations, we can tease out the degree to which the regulatory environment affects the risk. Thus, we are able to highlight regulatory risks as a mechanism through which climate and environmental risks and news affect security pricing.

Our paper also contributes to the literature on investor preferences for environmentally friendly securities such as the work on the emerging importance of green bonds (Baker et al., 2018; Flammer, 2021; Tang and Zhang, 2020; Zerbib, 2019; D'Amico et al., 2023; Pastor et al., 2022), and the pricing effect of ESG on sovereign bonds (Margaretic and Pouget, 2018; Capelle-Blancard et al., 2019). We

[8]See, for example, Heinkel et al. (2001); Pastor et al. (2021); Pedersen et al. (2021); Oehmke and Opp (2023); Goldstein et al. (2022); Dyck et al. (2019); Starks et al. (2022); Ilhan et al. (2023).

[9]For a review of the climate finance literature generally, see Gasparini and Tufano (2023).

show that ratings and spreads for corporate bonds as well as the institutional investor ownership of these bonds are affected by not only a firm's environmental activities but also their regulatory risk exposure. Similarly, our paper is related to work on some aspects of ESG and measures of bond risk and pricing (e.g., Jiraporn et al. (2014) and Amiraslani et al. (2022)). We differ through a focus on regulatory risk variation and through the use of a structural model to show that changes in volatility, rather than asset value, drive the changes we document in yield spreads.

Previous research shows the relation between firms' costs of debt and the liability and political uncertainty risks that they face (Gormley and Matsa, 2011; Bradley et al., 2016; Kaviani et al., 2020; Ilhan et al., 2021). Our paper is particularly complementary to that of Ilhan, Sautner, and Vilkov (2021), who examine the effects of the Paris Agreement on firms' tail risk by using out-of-the-money put options on firms' equity securities. They conclude that the Paris Agreement was followed by significantly increased tail risk for the top polluting industry firms. Our results on rating agencies' and bondholders' perceptions and actions combined with their results on equity holders' perceptions and actions support the hypothesis that climate regulatory risks are important factors in the pricing of both fixed income and equity securities. Significantly, our structural analysis allows us to examine the changes in both asset value and volatility surrounding an exogenous shock to firms' regulatory climate risk, the Paris Agreement, thus, directly testing the effects of the changes in regulatory uncertainty for the affected firms' securities.

Most importantly, our analysis and results deliver new insights into the question of how policy uncertainty, particularly policy uncertainty regarding climate change, affects firm risk. Policy uncertainty can affect firms' systematic risk as well as their idiosyncratic risks. Further, policy uncertainty has been shown to affect not only security returns (Pastor and Veronesi, 2013; Brogaard and Detzel, 2015; Kaviani et al., 2020), but also firms' investments and mergers and acquisitions (Gulen and Ion, 2016; Jens, 2017; Bonaime et al., 2018), among other effects (e.g., Baker et al., 2016). In our case we show how a particular type of policy uncertainty, regulatory uncertainty, can affect firms' corporate bond ratings and prices and hence, their cost of capital. These results also have broader policy implications given the relationship between the corporate bond market and the economy. For example, studies have found that not only are corporate bond returns strongly correlated with firm investments (Philippon, 2009), but that market distress can feedback into the real economy (Gilchrist and Zakrajšek, 2012; Gilchrist et al., 2014). Moreover, because of this relationship, policymakers have begun monitoring corporate bond markets for financial stability reasons. Boyarchenko et al. (2021) shows empirically that primary corporate bond market conditions can be an important source of predictive information for output, investment and employment not only for public firms, but also for the economy as a whole. Given that some central banks have begun to purchase corporate bonds as an important policy tool, our results could also have implications for central bank decision-making. For example, Papoutsi et al. (2022) show that the banks' bond portfolios overweight sectors with higher greenhouse gas emissions, which can affect optimal policy. Overall, our results are consistent with the arguments of Stiglitz et al. (2017) and Berg et al. (2023) that the uncertainty in the regulatory framework and path used by governments in the transition to combat climate change harms the efficiency of both financial institutions and financial markets.

2. Data

2.1. Sample construction

Our sample includes bonds issued by U.S. public non-financial companies over the 2009-2017 period, which are classified as corporate debentures and corporate medium term notes with maturities ranging from one month to 30 years.[10] We obtain data on these bonds and their issuing firms from a number of sources: Mergent FISD, Trade Reporting and Compliance Engine (TRACE), CRSP, Compustat, Sustainalytics and CDP.

We use the Mergent FISD database for characteristics of the bonds such as offering terms, maturity, the principal amount outstanding, and credit ratings (which originate from Moody's, Standard and Poor's (S&P) and Fitch). We employ the Moody's ratings as the primary source of credit ratings and transform the qualitative rating to a quantitative measure by assigning each rating a numerical value, giving a 1 to the lowest rating (D) and increasing by 1 for each notch such that the Moody's Aaa rating (or the S&P and Fitch equivalent) receives a value of 22.[11] This approach has the advantage that when a credit rating is downgraded, the representative number is

[10] We omit any non-standard corporate bonds such as Yankee bonds, convertible bonds, puttable bonds, exchangeable bonds, Canadian bonds, bonds listed in foreign currency, private placements, variable rate bonds and zero coupon bonds.

[11] If Moody's did not rate the security, we use the S&P rating and if that rating is also unavailable, we employ the Fitch rating.

lower.

Using the Mergent FISD offering terms, we define a bond's offering yield spread as the difference between a bond's offering yield and the yield of a cash flow-matched synthetic Treasury bond. In this measure the discount rates of varying maturities derive from the U.S. Treasury yield curve provided by Gürkaynak et al. (2007), where the yield of the synthetic Treasury bond is inverted from its price.

We combine the Mergent FISD bond characteristics data with data on secondary market pricing for corporate bonds from the TRACE database.[12] We calculate a bond's monthly yield as the median yield on all trades of that security occurring on its last active-trading day of a given month.[13] When possible, we linearly interpolate yields for months with missing yields. We then calculate trading yield spreads and the difference between a bond's trading yield and the yield of the Treasury bond with the same maturity in that month. Data on characteristics of the issuing companies are obtained through the CRSP and Compustat databases where we use the six-digit CUSIP to link companies across databases. We drop observations for which we are unable to obtain information on either the firm's headquarters location or the SIC industry code.[14]

Our first measure of the issuing firm's environmental profile relies on Sustainalytics Environmental Scores from their ESG rating service, which during this period are based on 57 environmental indicators and range from 0-100, with a higher score indicating stronger environmental performance. We employ the summary Environmental Score, which is calculated as a weighted average of the indicators, where the weights used are industry specific and proprietary, that is, the environmental scores are industry adjusted. We merge the corporate bond data with the Sustainalytics data at the issuer-year level using firm ticker symbols.

We derive three additional measures of a firm's environmental profile using firms' carbon emissions provided by CDP. Firms submit their carbon emissions data to CDP at the end of June each year, covering emissions for the previous year. The data includes information on Scope 1, Scope 2 and Scope 3 emissions, although not all firms that report to CDP provide the Scope 2 and Scope

[12] We adopt the procedure suggested in Dick-Nielsen (2009) to clean the TRACE data.

[13] Based on the suggestion in Edwards, Harris, and Piwowar (2007), all trades that deviate from the security daily median price by greater than 10% are dropped. Additionally, all price reversals greater than 10% are dropped.

[14] Headquarters location and SIC industry code are obtained from the Compustat. Since Compustat provides only current headquarter locations, we use historic headquarter locations provided by Gao (2020). Only 0.2% of the bonds in the sample are dropped because of missing headquarter or industry information.

3 emissions. Scope 1 emissions are direct emissions produced by the firm. Scope 2 emissions are indirect emissions from the generation of purchased energy. Scope 3 emissions are other indirect emissions that occur due to the firm's value chain. We focus on Scope 1 emissions as the firm has the most direct control over this type of emissions, and these emissions are measured with the most precision. Using the Scope 1 emissions data, we also calculate carbon intensity by dividing carbon emissions (in tons) by firm revenue (in thousands of dollars). We employ both total carbon emissions and carbon intensity in our tests.

Because not all firms submit their carbon emissions to CDP, we identify the highest carbon emission industries in the sample and for the difference-in-differences tests we employ an additional measure according to a firm's industry. Specifically, we rank industries by total carbon emissions within our sample, and define the industries with the top 15 carbon emissions as top carbon emission industries. We employ total industry emissions for this definition because political attention for climate regulations seems to focus on the size of total emissions rather than the carbon intensity.[15]

2.2. Environmental regulations data

U.S. environmental policy is designed as a shared responsibility between the federal government and the individual states—in general, federal environmental policies are established through laws passed by Congress and rules developed by the EPA. According to federal enforcement protocols, the individual states are authorized and expected to enforce EPA regulations for violations within the state. Thus, for most states, state government personnel evaluate compliance with the EPA regulations and issue enforcement actions if they come to the conclusion that the compliance standards are not being met. In addition, although states are allowed to create and enforce laws stricter than EPA regulations, they are also expected to handle enforcement at least as strictly as EPA standards. Since some states enforce regulations with the bare minimum standards and others enforce them more stringently, this allows us to observe cross-sectional variation in regulatory standards.

We obtain EPA enforcement data from the Integrated Compliance Information System for Fed-

[15] These industries are electricity, gas and sanitary, oil and gas extraction, transportation by air, petroleum and coal, chemical and allied products, primary metal, railroad transport, food and kindred products, paper and allied products, motor freight transportation, metal mining, general merchandise stores, stone, clay and glass, non-classifiable establishments, and transportation equipment.

eral Civil Enforcement Case Data. Employing this data we construct a measure of state-level environmental regulatory stringency that captures compliance and enforcement actions for the Clean Water Act (CWA), Clean Air Act (CAA) and Resource Conservation and Recovery Act (RCRA) in a given state in a given year. Our measure, which we adopt from the political science literature (Konisky, 2007), uses the number of enforcement actions, both informal enforcement actions with no pecuniary penalty (notifications of violation) and formal enforcement actions resulting in a pecuniary penalty for the firm (fines and administrative orders). We normalize the number of enforcement actions by the total number of facilities that are subject to EPA regulations in that state (measured in thousands), which is obtained from the Facility Registry Services (FRS).[16]

Because firms often have facilities in multiple states, we adapt the state-level EPA measures to firm-specific measures to capture the regulatory environment for individual firms. In order to determine each firm's aggregate exposure to state-level EPA enforcement, we use the National Establishment Time Series Database (NETs). The NETs is produced by Wall & Associates based on the Dun & Bradstreet dollar-directory database, and provides establishment-level information on firms, which we use to calculate each firm's revenue within each state in the United States. We then define the firm-level regulatory stringency as the weighted-average state-level environmental regulatory stringency across all of a firm's establishments.[17]

$$RegStringency_{j,t} = \sum_{s \in S_j} \left(\frac{StateRevenue_{j,s}}{TotalRevenue_j} \times EPAEnforcements_{s,t}\right), \tag{1}$$

where $TotalRevenue_j$ is total revenue by firm j in all states, $StateRevenue_{j,s}$ are total revenue by firm j in state s and $EPAEnforcements_{s,t}$ are total EPA enforcement actions in state s scaled by the number of EPA-registered facilities (in thousands) in state s at time t. Therefore, $RegStringency_{j,t}$ captures firm j's exposure to environmental regulatory enforcement at time t across the states within which the firm operates.

[16]If states fail to enforce regulations at the minimally acceptable level, the EPA has the option to enforce the laws themselves through their regional offices. States for which this is relevant are detailed at https://www.epa.gov/compliance/state-review-framework-compliance-and-enforcement-performance. Since we cannot observe whether the EPA or the state is the lead investigator on a given case, we drop all enforcement actions occurring in the few states in which the EPA is responsible for enforcement.

[17]For firms for which we cannot observe establishments in the NETs data, we use the total number of EPA enforcement actions for the state in which the firm's headquarters are located. We have also constructed alternative regulatory stringency measure based solely on the state in which the firm's headquarters reside. Our results hold.

2.3. Summary statistics

Our initial data set covers 5,548 bonds and 830 issuers contained in Mergent and TRACE databases over the 2009-2017 sample period. After merging the data with Sustainalytics, the sample size reduces to 4,235 bonds from 478 issuers. For the tests that employ the CDP carbon emissions data, we have 3,368 corporate bonds, corresponding to 287 issuers. In Table 1 we report the sample summary statistics. The average bond in the sample has a credit rating of about 15.3 (which is a little higher than a Baa1 rating) and an offering yield spread of 1.84%, and an average maturity of about 10 years. The average Environmental Score for the bond issuers is 60, above the halfway point of the 0-100 range. 48.7% of bond issues in the sample are from top 15 emissions industries.

The average issuing firm's carbon emissions is 6.68 million tons, but the median is only 0.44. The average carbon intensity is 0.32 tons of emissions per $1,000 in revenue, but the median is 0.01. These statistics reflect the fact that both carbon emissions and carbon intensity are highly positively skewed. Finally, the average $Reg_{j,t}$ for sample bond issuers is 0.71, indicating that, on average, 0.71 facility receives an enforcement action for every 1,000 facilities located in the same states as the issuer.

3. Credit risk, environmental profile, and regulatory stringency

3.1. Regression specifications

We first examine the relationship between bond credit risks and the issuing firms' environmental profiles, and whether that relationship is heightened by the firms' exposures to differing regulatory risks across states. In this set of analyses, we employ bond credit ratings and offering yield spreads as separate dependent variables that capture credit risk. The key independent variables in these regressions are firms' environmental profiles, the level of regulatory enforcement intensity each firm faces, and the interactions between these two variables. The specifications for bond i issued by firm

j at time t are as follows:

$$Rating_{ijt} = \beta_1 EnvProf_{jt-1} + \beta_2 Reg_{jt-1} + \beta_3 EnvProf_{jt-1} \times Reg_{jt-1} + \beta_4 X_{jt-1} + FE + \epsilon_{it}, \quad (2)$$

$$Spread_{ijt} = \beta_1 EnvProf_{jt-1} + \beta_2 Reg_{jt-1} + \beta_3 EnvProf_{jt-1} \times Reg_{jt-1} + \beta_4 X_{jt-1} + \beta_5 Z_{it} + FE + \epsilon_{it}, \quad (3)$$

where $EnvProf_{jt-1}$ is firm j's environmental profile at time $t-1$, which we proxy for using the Sustainalytics Environmental Score, the firm's total carbon emissions (in millions of tons), or the firm's carbon intensity (tons of emissions divided by revenue in thousands of dollars). Reg_{jt-1} is the regulatory stringency for firm j at time $t-1$, proxied by the revenue-weighted average state EPA enforcement intensity across a firm's establishments. X_{jt-1} are firm j's characteristics at time $t-1$ and Z_{it} are bond i's characteristics at time t. Firm characteristics include book leverage, pre-tax interest coverage, the natural log of total assets, cash-to-assets ratio, profitability, tangibility of assets, annual stock returns and standard deviation of stock returns. In the regression on ratings, we control for a firm's weighted-average maturity of all outstanding bonds at time t. In the regression on yields, we additionally control for bond characteristics such as principal amount, time to maturity, and an indicator for callable bonds. For all specifications, time fixed effects are used to control for macroeconomic trends. In some specifications, industry fixed effects are also included to control for time-invariant industry characteristics.

In Equations (2) and (3), the primary coefficient of interest is β_3, which captures the interaction effect between firms' environmental profiles and their regulatory conditions. Based on our hypothesis that firms with poor environmental scores tend to have higher regulatory risk exposure, we expect β_3 to be positive when credit ratings are the dependent variable. That is, conditional on a certain level of regulation, higher environmental scores imply the firm should be subject to less regulatory risk, and therefore higher credit ratings. Alternatively, when we employ the carbon emission measures in Equation (2), we expect β_3 to be negative since under conditions of stricter regulatory enforcement, higher carbon emissions imply more regulatory risk exposure, and therefore, lower credit ratings.

When we employ the bond's offering yield spread as the dependent variable in Equation (3), we expect the opposite signs on β_3 because yield spreads should be decreasing in regulatory risk exposure for higher environmental profile firms and increasing for high carbon emission firms.

We are also interested in the coefficient of $EnvProf$, β_1, as it captures the unconditional effect of a firm's environmental profile on its credit risk. Recent studies have shown that carbon risk seems to command a positive risk premium in the equity market (Bolton and Kacperczyk, 2021, 2022). If bond investors also care about carbon risk, we would expect credit ratings and yield spreads to differ across issuers with different environmental profiles, even for issuers exposed to average levels of regulatory risk.

In this set of analyses, we focus on at-issue bonds to better capture the relation between environmental regulatory risk exposure and firms' costs of debt because the offering spreads reflect the costs of issuing debt. Additionally, at-issue bond spreads are less noisy than trading yields, particularly given the general illiquidity of the secondary bond market.

3.2. Results

In Table 2 columns (1) through (3), we report the results for the regressions in which credit ratings are the dependent variables and we use time fixed effects. In column (1), using the firms' Sustainalytics environmental scores, we find that bonds issued by firms with higher environmental scores tend to have higher ratings. In particular, an increase in a firm's environmental score of one point is associated with a statistically significant 0.027 notch increase in credit ratings for firm-years with an average regulatory stringency.[18] Importantly, the interaction term between a firm's environmental score and the weighted-average regulatory stringency the firm faces is positive and statistically significant. When an increase in a firm's environmental score of one is combined with a one standard deviation increase in the firm's regulatory stringency, ratings increase by 0.047 notches (0.027 + 0.020). The results suggest that a firm's environmental profile affects its credit rating particularly through the channel of regulatory risks.

In the next two columns we employ the firm's carbon emissions in tons (column (2)) and carbon intensity (column (3)). For both of these measures, we find a strong negative effect of the interaction of the carbon emission measure and regulatory stringency on the firm's credit rating. Examining the result in column (3), If carbon intensity increases by one (ton per $1,000 revenue), a firm's credit rating decreases by 0.514 notch. This result suggests that carbon risk affects credit

[18]The standard deviation of the environmental score is 14.1.

ratings unconditionally. Moreover, when combined with a one standard deviation increase in *Reg*, the same increase in carbon intensity is associated with a 0.797 notch decrease in credit ratings ($-0.514 - 0.283$).

We include industry fixed effects in the regression-specifications in columns (4) through (6) of Table 2 in order to examine whether the relationship between a firm's environmental profile and credit risk is also present within a given industry. Column (4), in which we use the firm's environmental score, shows results similar to column (1), an increase in a firm's environmental score of one is associated with a 0.014 notch increase in their bonds' credit ratings. Moreover, when combined with a one standard deviation increase in firms' regulatory stringency, the same magnitude increase in environmental score is associated with an even larger increase in credit ratings: a 0.033 notch increase ($0.014 + 0.019$).

In column (5) using industry fixed effects, we now find a statistically significant negative relation between a firm's total carbon emissions and its credit ratings. In particular, a one million ton increase in a firm's carbon emissions is associated with a 0.014 notch decrease in its bond ratings. Moreover, if a firm operates in states with a one standard deviation increase in regulatory stringency, the same amount of additional carbon emissions is associated with a 0.035 notch decrease ($-0.014 - 0.021$) in credit ratings. Column (6) displays results using carbon intensity. An increase in carbon intensity of one (ton per $1,000 revenue) is associated with a 0.231 decrease in credit ratings. When combined with a one standard deviation increase in *Reg*, the carbon intensity increase is instead associated with a 0.559 decrease ($-0.231 - 0.328$) in credit ratings.

The results in Table 2 imply that credit rating agencies consider regulatory risk when evaluating how environmental concerns affect bond risk, which is consistent with rating agencies' policies. According to methodology published in 2018, credit rating analysts at Moody's consider both direct environmental implications and regulatory costs when evaluating ESG effects on credit ratings. Specifically, they state that they consider regulation more closely because forecasting is easier (Moody's, 2018). These statements are consistent with our finding that the effects of detrimental environmental activities on bond credit ratings are sensitive to the strictness of states' EPA regulation enforcement.

In Table 3, we present the regression results for the relationship between firms' offering bond spreads and their environmental risk exposures, where the regressions in columns (1) through (3) include results using only time fixed effects and columns (4) through (6) include both time and industry fixed effects. The results in column (1) indicate that a one unit increase in a firm's environmental score is associated with a 0.9 bp decrease in their bonds' offering yield spreads, holding the regulatory stringency a firm faces at the average level. Additionally, when a firm operates in states with a one standard deviation increase in EPA stringency, the same increase in environmental score is instead associated with a 1.4 bps decrease ($-0.9 - 0.5$) in offering yield spreads. Considering that the standard deviation of environmental score is 14.1, this effect is economically large. Our finding that firms with higher environmental scores have lower yield spreads is consistent with Chava (2014) who concludes that firms with higher environmental scores pay lower interest rates on their bank loans. Both our results and that of Chava (2014) imply that such firms face lower risks, which is an effect widely believed by many ESG investors.

The results in column (2) show that a one million ton increase in firm carbon emissions is associated with a 0.7 bp increase in yield spreads. When combined with a one standard deviation increase in *Reg*, the increase in emissions is associated with a 1.4 bps increase ($0.7 + 0.7$). Column (3) shows similar results when using carbon intensity as a carbon intensity increase of one (ton per $1,000 revenue) is associated with a 16.2 bps increase in bond spreads. These results are consistent with the argument that issuers with higher carbon emissions face higher costs in raising capital.

In columns (4) through (6), we report broadly similar results when employing both time and industry fixed effects. All three columns show that when combined with an increase in environmental scores, carbon emissions or carbon intensity, the offering yield spreads become higher. For example, column (5) show that a one million ton increase in carbon emissions, is associated with 0.9 bp higher spread for firms located in states where the EPA enforcement stringency is one standard deviation higher than average.

The results in Tables 2 and 3 show that bonds from firms with poor environmental performance tend to have both lower credit ratings and higher yield spreads. These results from the corporate bond markets are consistent with findings that carbon risk is priced into equity markets (Bolton and Kacperczyk, 2021, 2022). Importantly, these findings highlight that the effect is particularly pronounced when issuing firms have establishments in states with more stringent environmental regulation enforcement. The results imply that these firms face a higher probability of regulatory costs such as fines or possibly reputation losses, which in turn increases their credit risk.[19] The results, which are also consistent with previous research showing the greater negative consequences for firms that pollute under stricter regulatory regimes, imply strictness in regulation forces firms to internalize the costs of pollution (Greenstone, 2002).

The results are also informative about the channel through which environmental regulations affect credit ratings and yield spreads. In particular, these findings show that environmental regulatory risk is related to credit ratings and yields spreads both across-industry and within-industry, which suggests that for the high carbon emission sectors, firms that operate in states with stricter regulatory enforcement likely bear even more credit risk than their counterparts in less stringent states.

4. The Paris Agreement announcement

A firm's environmental profile and its regulatory conditions may be jointly determined, thus, creating potential endogeneity issues. For example, state governments could impose stricter environmental regulations because the economic conditions in the state are favorable; these favorable economic conditions might in turn attract high carbon emission firms to locate there. To mitigate such endogeneity concerns, we exploit an event that increases the climate regulatory risks faced by firms, while changing neither the performance nor the environmental profiles of these firms.

4.1. The Setting: The Paris Agreement and the Clean Power Plan

The setting we use in our research design is the passage of the Paris Agreement, announced on December 12, 2015. The Paris Agreement had the primary goal of limiting global temperature rise in this century to 1.5 degrees Celsius above pre-industrial levels. To achieve this goal, the Agreement calls for the signing countries to submit national action plans to reduce emissions with sufficient speed to achieve the goal. Such plans imply the development of expectations that more stringent environmental regulations are likely to be imposed in the future, since the national action plans would need to include regulatory responses to induce firms to help achieve the climate goal.

[19]These results are consistent with the legal cost evidence provided by Karpoff et al. (2005). Although the authors of this article conclude there exist no reputational losses for EPA violations during their sample period, investors, including institutional investors, have become much more concerned about firms' environmental activities over the approximately two decades since their sample ended.

Many countries were preparing changes prior to the December 2015 meeting. For example in the US, the Paris Agreement announcement was preceded on August 3, 2015, by the Obama administration's announcement of the Clean Power Plan, which used the EPA's authority under the Clean Air Act to regulate carbon emissions. Under this Plan, the EPA assigned each state a goal for limiting emissions from existing power plants. The Plan also increased regulatory requirements for building new power plants, and in particular made it very difficult to build new coal plants. The EPA estimated this Plan would reduce greenhouse gas emissions from the power sector 32 percent below 2005 levels by 2030. Market participants likely viewed this Plan as credible, as the action was opposed by fossil fuel and utilities companies as well as 24 state attorney generals due to the high costs associated with phasing out coal plants and transitioning to other energy sources. Moreover, the Obama administration advertised the Clean Power Plan during the Paris climate talks, indicating that the Plan was seen as an important US regulatory response to meet the Paris Agreement goals.

We hypothesize that the passage of the Paris Agreement would have raised an expectation of more climate regulation stringency in the U.S., most immediately through the channel of the Clean Power Plan. Given the existence of the Clean Power Plan and the uncertainty surrounding its implementation, the announcement of the Paris Agreement would elevate the climate regulatory risks for firms with high carbon footprints. The increased level of risks should then be reflected in changes in firms' bond credit ratings and spreads. To test this hypothesis, we conduct difference-in-differences analyses to compare changes in the credit ratings and yield spreads of bonds from firms with problematic environmental profiles versus those from other firms, both before and after the Paris Agreement.

4.2. Descriptive evidence of changes in bond credit ratings and spreads

We start by visually inspecting changes in the average credit ratings and spreads for bonds issued by firms in high carbon-emitting industries and by firms with different environmental scores. Figure 1(a) displays the average credit ratings for each of the top 15 carbon-emitting industries before and after the December 2015 Paris Agreement. Prior to the Paris Agreement, issuers in industries such as petroleum and coal products or motor freight transportation tend to be more creditworthy, on average, while other high carbon emission industries, such as stone, clay and glass or metal mining, appear to be less creditworthy, on average.

Figure 1(a) shows a clear pattern that the Paris Agreement is associated with a ratings decrease for firms in high carbon emission industries. In particular, some of the high-carbon emitting industries whose ratings are most affected by the announcement of the Paris Agreement (such as primary metal and metal mining) are relatively less sensitive to oil prices, suggesting that the effect is unlikely driven by any concurrent changes in oil prices (an issue we examine in more depth later in the paper).

Figure 1(b) shows changes in yield spreads for bonds issued by firms in the top 15 carbon-emitting industries before and after the Paris Agreement. As in the case of the credit ratings, substantial differences exist across industries in the magnitude of the yield spreads and their changes. Nonetheless, in most cases, large increases in spreads occurred after the Agreement with the largest increases in primary metals, water transport, oil and gas extraction and metal mining industries.

In Figures 2(a) and 2(b), we illustrate average credit ratings and yield spreads by environmental score bins for the periods before and after the Paris Agreement. Issuers are sorted by their December 2014 Sustainalytics Environmental Score into eight groups.[20] Figure 2(a) shows the average credit ratings for each group before and after the Paris Agreement. The figure clearly demonstrates that, after the Paris Agreement, the average credit ratings decrease substantially for bonds from firms with lower environmental scores, whereas there appears to be little effect for bonds from firms with higher environmental scores.

Similarly, Figure 2(b) displays the average yield spreads for bonds across the environmental score bins. Again, the figure shows a material increase in yield spreads around the Paris Agreement for issues from firms with environmental scores below 60, and very little change for those with environmental scores above 60. These figures are consistent with our hypothesis that the Paris Agreement led to perceptions of increased regulatory risk resulting in lower credit ratings and higher bond yield spreads, on average, for firms with low environmental scores.

[20]Note the Sustaintalytics data does not include any United States firms with environmental scores below 20.

4.3. Tests for changes in credit ratings around the Paris Agreement

We first test changes in bond credit ratings in the two-year period around the December 2015 Paris Agreement through the following difference-in-differences regression:

$$Rating_{it} = \beta_1 EnvProf_j \times AfterParis_t + \gamma_i + \kappa_t + \epsilon_{it}, \tag{4}$$

where $AfterParis_t$ is an indicator variable for the months starting in December 2015 and continuing through the following 12 months. We include time fixed effects, κ_t, and security fixed effects, γ_i. Since the Paris Agreement is a time-series shock, our sample in these tests consists of bonds issued before the Paris Agreement in order to capture changes in ratings influenced by the Agreement.[21] In constructing our test sample, we include a pre-event period of twelve months prior to the Agreement and a post-event period of twelve months following the Agreement. That is, the testing period runs from December 2014 through November 2016.

We employ four measures of a firm's environmental profile. First, we use an indicator variable equal to one if a firm is in the top-quartile in terms of firm-level total carbon emissions in 2014. Second, we use an indicator variable equal to one if a firm is in the top-quartile in terms of firm-level carbon intensity in 2014. Third, we use an indicator variable for whether a firm is in one of the top 15 carbon-emitting industries. Finally, we use an indicator variable equal to one if a firm has a below-median environmental score in December 2014.

In Equation (4) β_1 captures the change in bond risk assessments around the Paris Agreement for a firm with a poor environmental profile relative to other firms, controlling for time-invariant bond characteristics and for macroeconomic trends that affect all bond issues. We double-cluster standard errors at the 3-digit SIC industry and month levels to account for correlated error terms within industries and across time.

Table 4 reports the results of the difference-in-differences regressions. Column (1) shows that after the Paris Agreement, bond ratings decreased by 0.51 notch for bonds issued by firms with top-quartile emissions relative to other firms. Based on this result, the Paris Agreement led to an economically significant decrease in bond ratings for firms with higher emissions relative to

[21] Specifically, the sample includes bonds issued at least one year before the Paris Agreement, i.e., in December 2014 or earlier. We also require that the bonds do not mature before the end of the sample period.

other firms. Column (2) instead examines firms with top-quartile carbon intensity, where bond ratings decrease by 0.63 notch for those bonds relative to others. Column (3) shows there was not a statistically significant change in credit ratings for bonds issued by firms in high emission industries relative to others. Lastly, column (4) examines bonds issued by firms with below median environmental scores, whose credit ratings decreased by 0.6 notch relative to bonds issued by firms with higher environmental scores. Regardless of the measure used, corporate bond ratings decreased after the Paris Agreement for bonds issued by firms exposed to more climate risk relative to bonds from other issuers. Moreover, as shown by the results using the environmental score in the first column, bond ratings decreased after the Paris Agreement for bonds issued by firms exposed to environmental risk more generally.

We examine the dynamics of the treatment effects in relation to the Paris Agreement event. Specifically, we construct a series of tests to examine the time series of differences between ratings for firms in the treatment and the control groups. We run the following regressions:

$$Rating_{it} = \sum_{k=-11}^{11} \beta_k [\mathbb{1}(t = k) \times EnvProf_j] + \gamma_i + \kappa_t + \epsilon_{it}, \tag{5}$$

where $\mathbb{1}(t = k)$ are indicators for periods that are k months after (or before) the Paris Agreement. The time indicator variable for the first month in our sample period (December 2014) is excluded, so all treatment effects are relative to December 2014.

Figure 3 shows the dynamics of the credit ratings of treated firms relative to control firms around the Paris Agreement. Panel (a) displays the treatment effects over time for bonds issued by firms with top-quartile emissions. The solid line and dots indicate the coefficient estimates, and the dashed lines represent bands of a 90% confidence interval around these estimates. We find no significant differences in the treatment effect in the entire period before the Agreement, indicating the parallel trends assumption appears to hold. In contrast, after the Agreement, the treated firms' bonds have significantly lower credit ratings, consistent with the results reported in Table 4. Figures 3 (b), (c) and (d) illustrate the results for Equation (5) when the treated firms with top-quartile carbon intensity, in a top 15 carbon emitting industry or with a below-median environmental score, respectively. All of the figures show a significant drop of treated firms' credit ratings after the Paris Agreement.

The findings in this section imply a direct consequence of the Paris Agreement for firms with problematic environmental profiles. In particular, they provide evidence that credit rating agency analysts appear concerned about future regulatory changes when evaluating the effects of environmental risk on a bond's default risk.

4.4. Tests for changes in bond yield spreads around the Paris Agreement

To test for changes in bond yield spreads around the Paris Agreement we use the following regression:

$$Spread_{it} = \beta_1 EnvProf_j \times AfterParis_t + \gamma_i + \kappa_{tp} + \epsilon_{it}, \tag{6}$$

where we measure a firm's environmental profile using the same four measures as in Equation (4). Instead of employing a time fixed effect, we include a matched-pair-by-time fixed effect κ_{tp}, where the matching procedure is described in more detail below. As a result, this test can be interpreted as comparing the change in spread for a treated security to its matched control security after the Paris Agreement, controlling for time-invariant security characteristics.

To better control for noise in spreads and to compare bonds with similar creditworthiness, we conduct a one-to-one Mahalanobis matching with replacement. The purpose of this matching approach is to identify and match every treated bond to the most similar control bond according to various covariates.[22] This distance is calculated as of year-end 2014 using the bond's credit rating, the bond principal outstanding, the bond's time to maturity, and the firm's equity oil beta.

We believe it is particularly important to match on oil beta in order to alleviate a potential concern that changes in bond pricing may be driven by concurrent movements in the oil market, particularly given the volatile changes in oil prices over this period.[23] We use the following model to calculate firms' equity oil betas:

$$R_{it} = \alpha + \beta_{market} MktRet_t + \beta_{oil} OilRet_t, \tag{7}$$

where $MktRet$ is proxied by the CRSP value-weighted index and $OilRet_t$ is the monthly return

[22] We use a caliper of 1, meaning if for a given treatment firm there does not exist a control firm whose Mahalanobis distance is 1 or less, we drop the firm from the sample. We further address the potential bias in continuous variable matching using the methods proposed by Abadie and Imbens (2006).

[23] Generally speaking, oil price volatility is seen as negatively predicting economic growth and aggregate equity prices, especially for the oil sector (Gao et al., 2022).

on Brent Crude Oil for month t. We calculate this value for each firm in our sample for which we observe 36 months or more of stock price data before November 2015.

We construct four matched samples, one for each of our environmental measures, the below-median environmental score, the top carbon emission industry, the top emission quartile and the top carbon intensity quartile treatments, respectively. In Table A.1 we report the summary statistics for all matched samples (as of the matching date). Panels A, B, C, and D report statistics for the control and treated groups matched on each treatment. The last column of each panel provides difference-in-means tests between the treated and control groups. As the differences between these two groups are generally statistically insignificant and economically small, it is reasonable to conclude the treated and control groups are observationally similar.

Table 5 reports the results from the difference-in-differences regression in which bond spread is the dependent variable. The effects of the Paris Agreement on the treated firms' spreads are both economically large and statistically significant. Column (1) indicates that after the Paris Agreement, bond yield spreads increased by 30.1 bps for bonds issued by firms with top-quartile emissions. Similar results are observed when examining bonds issued by firms with top-quartile carbon intensity or in high-emitting industries, whose yield spreads increased by 34.7 bps and 38.6 bps, respectively. Lastly, column (4) displays results using the below median environmental score indicator, which shows that yield spreads increased by 39.4 bps for these bonds relative to others.[24] These results provide evidence that regardless of the specific firm environmental profile measure used, after the Paris Agreement corporate bond spreads increased for bonds issued by firms with poor environmental profiles relative to other firms.[25]

We further provide visual evidence for the parallel trend assumption by running the following dynamic difference-in-differences regression:

$$Spread_{it} = \sum_{k=-11}^{11} \beta_k [\mathbb{1}(t = k) \times EnvProf_j] + \gamma_i + \kappa_{tp} + \epsilon_{it}. \quad (8)$$

The excluded period is December 2014. Additionally, we use security and matched-pair-by-time

[24] In untabulated results we also conducted the analysis using the full unmatched sample, and the results not only continue to hold, but they are also larger in magnitude.

[25] To examine robustness of the results according to matching specification, Figure A.1 displays a sensitivity analysis varying the matching by caliper and controls. Details of the specifications are described in Table A.2.

fixed effects.

Figure 4(a) illustrates the changes in bond spreads around the Paris Agreement using a top-quartile emissions indicator as the treatment. Prior to the Paris Agreement, there does not appear to be a substantial differential increase in bond spreads for issuers with high emissions relative to other issuers. Additionally, right after the announcement of the Paris Agreement, there exists a significant and sizable increase in spreads for bonds issued by firms with top-quartile emissions scores relative to other bonds. Similar patterns are observed for high carbon intensity firms in Figure 4(b), firms in top carbon emitting industries in Figure 4(c) and firms with below median environmental scores in Figure 4(d). However, in these figures, there appears to be some anticipatory effect prior to the Paris Agreement, especially around August 2015. We ascribe this anticipatory effect to the announcement of the Clean Power Plan at the beginning of that month, which provided market participants some initial news that regulatory costs could increase going forward.

The initial increase in yield spreads for firms with significant carbon footprints largely reversed in the months after the Paris Agreement, beginning in February 2016. One explanation for the reversal is that, immediately after being announced, the Clean Power Plan was challenged in the courts by 24 states with the support of industry groups. In response to this challenge, on February 9, 2016, with a 5–4 vote, the US Supreme Court ordered the EPA to suspend enforcement of the Plan until the lawsuit could be reviewed by the Appeals Court.[26] This Supreme court ruling created uncertainty over whether the Plan would be enacted until after the Presidential Election 9 months later. Our yield spread figures show that the credit spread increase is muted but still detectable until November 2016. In November 2016, Donald Trump, who campaigned on pulling the U.S. out of the Paris Agreement, won the election. The Trump administration ultimately ordered the EPA to dismantle the Clean Power Plan, and also pulled out of the Paris Agreement, which explains the eventual complete reversal of the effect.

4.5. Triple-difference tests around the Paris Agreement

While the Paris Agreement increased the prospect of future environmental regulatory risks, we expect its effects to differ across companies in part due to variations across state governments in their enforcement of environmental regulations. In a scenario in which the U.S. government

[26]See https://www.climatecentral.org/news/obama-confident-climate-plan-court-setback-20014.

imposes new environmental regulation at the federal level, we hypothesize that firms located in high-enforcement states should have greater effects on their credit ratings and bond yield spreads because the regulatory environments in these states would be more likely to impose stricter regulatory requirements. To examine this hypothesis, we conduct a triple-difference regression in which we include an indicator variable for firms with stricter regulatory environments. To define the stricter regulatory environments, we sort firms by *Reg*, which is calculated as firm's revenue-weighted average environmental regulatory strigency, from 2012 through 2015 (the four years leading up to the Paris Agreement). Firms with a top-quartile *Reg* are defined as high regulatory enforcement firms.

Using these definitions, we run the following analyses:

$$\begin{aligned} Rating_{it} = \gamma_i + \kappa_t &+ \beta_1 AfterParis_t \times EnvProf_j + \beta_2 AfterParis_t \times HighReg_j \\ &+ \beta_3 EnvProf_j \times HighReg_j + \beta_4 AfterParis_t \times EnvProf_j \times HighReg_j + \gamma_i + \kappa_t + \epsilon_{it}, \end{aligned} \tag{9}$$

and

$$\begin{aligned} Spread_{it} = \gamma_i + \kappa_{tp} &+ \beta_1 AfterParis_t \times EnvProf_j + \beta_2 AfterParis_t \times HighReg_j \\ &+ \beta_3 EnvProf_j \times HighReg_j + \beta_4 AfterParis_t \times EnvProf_j \times HighReg_j + \gamma_i + \kappa_{tp} + \epsilon_{it}, \end{aligned} \tag{10}$$

where $HighReg_j$ is an indicator variable for high regulatory enforcement firms.

The primary parameter of interest, β_4, captures the effects of the Paris Agreement for firms with poor environmental profiles that operate in states with strict regulatory enforcement relative to firms that operate in less stringent states. If after the Paris Agreement firms with poor environmental profiles become more exposed to climate regulatory risks in states where any potential new regulations are expected to be enforced more strictly, we expect β_4 to be negative in the credit rating regressions and positive in the yield spread regressions. Such a result would suggest that regulatory risk is the channel through which the Paris Agreement affects bond credit ratings and spreads. We again use four alternative measures to define treated firms.

Table 6 provides the results of the triple-difference regressions where the dependent variable is credit rating. The main parameter of interest is the coefficient for the triple-difference estimator

$AfterParis_t \times EnvProf_j \times HighReg_j$. In Column (1) in which the environmental measure is the top-quartile emissions indicator, the results show that after the Paris Agreement, relative to the firms located in low regulatory stringency states, firms with the most carbon emissions located in strict regulatory states experienced credit rating decreases of an additional 1.37 notch. Results in other columns show that after the Paris Agreement, if an issuing company is located in a high regulatory enforcement state, bond ratings decrease by an additional 1.39 notch, 1.09 notch, and 0.99 notch for bonds issued by firms in the top-quartile of carbon intensity, in high-emitting industries and with below median environmental scores, respectively. Overall, the results imply that the decrease in corporate bond ratings following the Paris Agreement is driven by firms with operations in states that have stricter regulatory enforcement.

Table 7 reports the results for the triple-difference tests when bond spreads are the dependent variables. Columns (1) and (2) display results using the top-quartile emissions and top-quartile carbon intensity indicators, which are statistically insignificant. Column (3) displays results for the high carbon emission industry indicator and the results are similar. Bond spreads increase by an additional 70 bps for bonds issued by firms in high carbon emission industries if the firm is located in stricter regulatory enforcement states. Column (4) displays results using the below-median environmental score indicator. Bond spreads increase by an additional 91.1 bps for firms with poor environmental profiles and located in stricter regulatory enforcement states, as compared with poor-environmental firms located in less strict states.

The triple-difference results indicate that most of the effect of the Paris Agreement on firms' cost of debt arises through the regulatory cost channel. Both credit rating analysts and bond investors seem to believe that the Paris Agreement would have greater effects on issuers located in high-regulation states. These results support our hypothesis that bond market participants expected the Paris Agreement to lead to increased regulations for environmentally problematic firms and that the new regulations would most likely be enforced through the state governmental agencies.

5. Interpreting the Paris Agreement results through a structural credit model

In this section, we interpret the yield spread changes around the Paris Agreement by estimating a structural model based on Merton (1974). A structural model helps in understanding the underlying economic mechanisms around yield spread changes, as previous literature (e.g., Schaefer and Strebulaev, 2008; Huang, Shi, and Zhou, 2020) shows that structural credit models fit the elasticity of credit spreads to equity well in the data. This analysis allows us to interpret the observed yield spread changes of firms with high carbon footprints (i.e. the treated firms) jointly with their equity returns, which have been shown in previous research to decline after the Paris Agreement announcement (Monasterolo and de Angelis, 2020; Mukanjari and Sterner, 2018). In addition, we can gain additional insights by decomposing the changes in yield spreads to the portion related to changes in issuer asset value and the portion related to changes in issuer asset volatility.

5.1. The Merton (1974) Model

Consider the classic Merton model, in which the firm's asset value follows a Brownian motion:

$$\frac{dV_t}{V_t} = (r - \delta)dt + \sigma dW_t, \tag{11}$$

where σ is asset volatility and δ is the corporate payout ratio. A firm's equity can be considered a call option on the asset value in this context, where:

$$V_E = VN(d_1) - Ke^{-rT}N(d_2), \tag{12}$$

and:

$$d_1 = \frac{ln(V/K) + (r - \delta + \sigma^2/2)\tau}{\sigma\sqrt{\tau}}, \tag{13}$$

$$d_2 = d_1 - \sigma\sqrt{\tau}. \tag{14}$$

As a first pass, we want to evaluate whether in the Merton model the observed joint movements of poor environmental firms' securities in the equity and bond markets are driven by random shocks

dW_t or by structural breaks. If the underlying parameters of the model, including asset volatility σ, do not change, then the sensitivity of credit spreads with respect to equity returns can be expressed as follows:

$$h_E^{CS} := \frac{\partial(CS)}{\partial E/E} = -\frac{1}{\tau}(\frac{1}{N(d_1)} - 1)(\frac{1}{L} - 1). \tag{15}$$

Under the assumption of no structural changes, based on the observed (percentage) equity return r_i^e after the Paris Agreement on issuer j's equity, we should expect the same firm's bond issue to change its credit spread by the amount of ΔCS_i^*:

$$\Delta CS_i^* = \frac{1}{\tau}(\frac{1}{N(d_1)} - 1)(\frac{1}{L} - 1)r_i^e. \tag{16}$$

5.2. Do equity returns explain the change in yield spreads without structural breaks?

In this section we examine whether the change in equity returns following the Paris Agreement was sufficient to explain the changes in bond yield spreads without corresponding changes in the Merton model's structural parameters. To conduct this analysis, we first estimate the Merton model parameters using data from the period before the Paris Agreement. We then calculate a model-implied change in bond yield spreads conditional on observed equity returns using Equation 16. Comparing the model-implied credit spread changes to the observed credit spread changes for firms affected by the Paris Agreement allows us to understand whether a firm's asset value V and asset volatility σ changed following the Paris Agreement.

To estimate each issuer's Merton model parameters for the period before the Paris Agreement, we employ the methodology of Vassalou and Xing (2004). Assuming that the relationship between issuer equity, debt and asset value follows the Merton (1974) model, we calculate σ through an iterative procedure, which uses daily equity return data from the past 12 months to estimate equity volatility as the initial value for estimating σ.[27] From Equation 12, with V_E as the market value for each trading day in the past 12 months, we compute V. Using these V's, we calculate asset returns and their resulting standard deviation, which becomes the value of σ for the next iteration.

[27] In this procedure, we use the total debt for an issuer in Compustat as K, the sum of Compustat interest, dividends and repurchases scaled by total assets as δ, the one-year Treasury bond rate as r, and the bond time to maturity from Mergent as τ. If the total debt is missing or equal to zero in Compustat, we use the issuer's total bonds principal outstanding from Mergent.

We repeat this process until the values of σ from two iterations converge to within 1×10^{-4} of each other. From the converged value of σ, we calculate V.

We compute these V's and σ's as of November 2015 (i.e. the month before the Paris Agreement) and refer to them as V^{pre}, σ^{pre}. We then employ these values in Equation 16 to calculate the model-implied change in bond yield spreads, conditional on pre-Paris asset values and volatilities. A histogram of the change in model-implied bond yield spreads is plotted alongside the change in actual bond yield spreads in Figure 5. Red and blue solid lines are shown to indicate average changes in actual spreads and model-implied spreads, respectively. Dashed red and blue lines show the 90% confidence intervals, respectively. Examining these figures, it is apparent that model-implied changes in bond yield spreads are on average smaller than observed changes in bond yields. Two-sided t-tests show that these differences are statistically significant at the 1% level. We conclude from this analysis that the underlying parameters of the credit model must have changed after the Paris Agreement. To better understand what drove the change in yield spreads, we next examine how asset values and volatilities changed after the Paris Agreement.

5.3. Estimating the changes in asset values and volatilities

From the Merton model, a firm's equity value and credit spread can be written as follows:

$$E(V, \sigma) = VN(d_1(V, \sigma)) - Ke^{-\tau r}N(d_2(V, \sigma)), \tag{17}$$

$$CS(V, \sigma) = -\frac{ln[VN(-d_1(V, \sigma))e^{\tau r}/K + N(d_2(V, \sigma)]}{\tau}. \tag{18}$$

Given our estimated pre-Paris structural parameters V^{pre} and σ^{pre} for each firm using the iterative method, we can calculate the firm's equity value $E(V^{pre}, \sigma^{pre})$ and bond credit spread $CS(V^{pre}, \sigma^{pre})$ just before the Paris Agreement. We define a firm's target post-Paris equity value as its pre-Paris equity value multiplied by the observed equity return between the Paris Agreement announcement and t month(s) afterwards:

$$E^{post}(V^t, \sigma^t) := E(V^{pre}, \sigma^{pre})(1 + r_t^e), \tag{19}$$

and a firm's target post-Paris credit spread as its pre-Paris credit spread plus the observed credit spread change during the Agreement:

$$CS^{post}(V^t, \sigma^t) \coloneqq CS(V^{pre}, \sigma^{pre}) + \Delta CS^t. \tag{20}$$

The remaining question is then what new values of V^t and σ^t are compatible with the post-Paris Agreement equity value $E^{post}(V^t, \sigma^t)$ and credit spread $CS^{post}(V^t, \sigma^t)$? Using Equation 17 and Equation 18 we derive the following equations:

$$E^{post}(V^t, \sigma^t) = V^t N(d_1(V^t, \sigma^t)) - Ke^{-\tau r} N(d_2(V^t, \sigma^t)), \tag{21}$$

$$CS^{post}(V^t, \sigma^t) = -\frac{ln[V^t N(-d_1(V^t, \sigma^t)) e^{\tau r}/K + N(d_2(V^t, \sigma^t)]}{\tau}. \tag{22}$$

We solve this nonlinear system of equations for each of the six months after the Paris Agreement ($t = 1, 2, 3, ..., 6$) to find V^t, σ^t.[28] Note that as described in Schaefer and Strebulaev (2008), credit yield spreads contain both a credit and non-credit component, whereas Merton (1974) models the credit component. To address this point, we instead solve this system of equations using as the credit-component of the change in credit spreads calculated with the methodology in Longstaff et al. (2005).

After solving for V^t and σ^t for each issuer, we calculate the changes in asset values and volatilities for each of the six months after the Paris Agreement ($t = 1, 2, 3, ..., 6$) for every bond in the sample:

$$\Delta V^t = \frac{V^t - V^{pre}}{V^{pre}} \tag{23}$$

$$\Delta \sigma^t = \sigma^t - \sigma^{pre} \tag{24}$$

Then, for each given time horizon t, we examine treated firms' differential changes in asset value

[28] This system of nonlinear equations is solved in MATLAB, which requires an initial value for the asset value and volatility. Firms' Pre-Paris Agreement model asset values are the initial values for the firms' asset values. The initial values for the firms' volatilities are computed based on the methodology in Feldhütter and Schaefer (2018). Specifically, we estimate $(1 - L_t)\sigma_{E,t}$, where L_t is market leverage and $\sigma_{E,t}$ is volatility of equity returns, and multiply this by 1 if $L_t \leq 0.25$, 1.05 if $0.25 < L_t \leq 0.35$, 1.10 if $0.35 < L_t \leq 0.45$, 1.20 if $0.45 < L_t \leq 0.55$, 1.40 if $0.55 < L_t \leq 0.75$ and 1.80 if $L_t > 0.75$, and use the final product as our initial value.

and asset volatility relative to control firms by running the following regressions:

$$\Delta V_i^t = \beta EnvProf_j + \kappa_p + \epsilon_i, \quad (25)$$

$$\Delta \sigma_i^t = \beta EnvProf_j + \kappa_p + \epsilon_i, \quad (26)$$

where κ_p are matched-pair fixed effects. Just as in the difference-in-differences analysis, $EnvProf_i$ is an indicator equal to one if an issuer is in the top-quartile of carbon emissions, in the top-quartile of carbon intensities, in a top-15 carbon emitting industry, or has a below median environmental score, and otherwise, zero. Since these tests are based on the model-implied asset values and volatilities, they can be interpreted as describing how much of a change in asset value and volatility would have been needed to explain the observed changes in bond yield spreads and equity values.

Results from these regressions on changes in asset values are plotted in Figure 6. Panel (a) displays results using the firm being in the top quartile of emissions category to proxy for its environmental profile. For this group of bonds, we find the changes are not statistically significant. Panel (b) displays results using the firm's carbon intensity as the environmental profile proxy. The results indicate a drop of about 2.5% in asset value in the month after the Paris Agreement, that subsequently reverses. Panels (c) and (d) show results using the top-15 emitting industries and below median environmental score, respectively. In neither case is the effect statistically significant.

The first four columns of Table 8 provides the magnitudes for the regressions at the 1, 3 and 6 month time horizons. Panel A shows that at the 1-month horizon, there is a statistically significant drop in asset values for bonds with top-quartile carbon intensities relatively to others. Under other specifications, the change in asset value does not appear to be statistically significant. The point estimate reverts back to zero at the 3-month horizon. These results show that the model-implied changes in asset values following the Paris Agreement were modest.

Figure 7 illustrates the plots for changes in asset volatilities. Panel (a) uses the top quartile emission firms as treated issuers and shows that asset volatilities increase by about 0.15 for high-emitting borrowers relative to others in the two months following the Paris Agreement. As of 6 months after the Paris Agreement, asset volatilities are still about 0.1 larger for high-emitting issuers relative to others. Panels (b) and (c) display plots using the top quartile carbon intensities and top 15 emitting industries, which show similar results. Panel (d) displays results using the below median environmental score indicator, which shows no differential increase in asset volatilities for treated bonds, perhaps because this indicator is relatively less directly connected to climate regulatory risks. Columns (5) through (8) of Table 8 reports the magnitudes of the regression results at the 1, 3 and 6 month time horizons. We observe a 10-15 percentage point increase in asset volatilities of high carbon emitting firms at the 3-month horizon. The model-implied changes in asset volatilities following the Paris Agreement are relatively persistent and remain detectable at the 6-month horizon.

These results provide evidence that asset values and volatilities changed differentially for affected bonds relative to others after the Paris Agreement. The relative weakness and eventual reversal in the changes in asset values juxtaposed with the persistence of the changes in asset volatilities suggests that the changes in bond yield spreads after the Paris Agreement arise primarily from the changes in asset volatilities. These effects could be due to the fact that the Clean Power Plan, the primary initial tool for the US to enact the Paris Agreement goals, was put on hold in February 2016, which created uncertainty over whether regulation to implement the Paris Agreement goals would continue to exist if a Republican was elected as President. Thus, the uncertainty would remain until the November 2016 election. This interpretation is consistent with previous literature showing that political uncertainty affects asset prices (Pastor and Veronesi, 2013). Specifically, these results imply that even in the absence of implementation of climate policies, uncertainty over those policies can affect corporate bond markets.

5.4. *Probabilities of default*

In this section we test whether the changes in bond yield spreads can be explained more by the changes in asset values or changes in asset volatilities by examining how these model estimates translate into changes in the bonds' probabilities of default. To do this, we calculate a model-implied probability of default using the estimated values of V^t and σ^t:

$$DD = \frac{ln(V/K) + (\mu - \sigma^2/2)T}{\sigma\sqrt{T}} \tag{27}$$

$$P(default) = 1 - N(DD), \tag{28}$$

where DD is the model-implied distance to default, μ is the expected growth rate of assets, which is calculated using maximum-likelihood estimation on the bond issuer's historical equity return. In addition to the model-implied probability of default, we calculate two counterfactual probabilities of default. In the first counterfactual calculation, we use the model-implied asset value while holding the asset volatility constant at its pre-Paris estimate. In the second counterfactual calculation, we use the model-implied asset volatility while holding the asset value constant at its pre-Paris estimate. This approach allows us to estimate how much the changes in asset values and volatilities mattered to bond investors.

We tabulate the change in probability of default for bonds issued by firms in the top-quartile of emissions and matched control bonds in Table 9. Panel A displays all bonds, regardless of their rating. Prior to the Paris Agreement, there was no substantial difference in the probability of default for treated and matched control bonds. However, after the Paris Agreement, there was an increase of 1.84% in the probability of default for bonds issued by firms with high emissions relative to others. This result shows that the changes in bonds issued by high-emitting firms following the Paris Agreement translated into increases in the probability of default. Moreover, Panels B and C divide the sample into investment grade bonds and noninvestment grade bonds, and show that the majority of the effect is from bonds rated below investment grade. This difference in changes between the investment grade and noninvestment grade bonds highlights the potential challenges to financial stability, as these bonds are the ones that are more likely exposed to risk of financial distress ex-ante.

Figure 8 shows the plots (in blue) for the estimated probabilities of default for bonds issued by firms with high emissions. The default probability of treated bonds sharply increased after the Paris Agreement, reaching a peak of 2.3%, before starting to decrease in February, 2016. Furthermore, the default probability does not completely decrease to its original value, but instead remains elevated for at least six months. This increase in the probability of default is economically meaningful as corporate bond prices are strongly correlated with firm investment (Philippon, 2009). For this reason, market distress can feedback into the real economy and can lead to reduced investment by firms (Gilchrist and Zakrajšek, 2012; Gilchrist et al., 2014).[29]

[29] These relationships are so meaningful that policymakers have begun monitoring corporate bond markets for financial stability reasons (Boyarchenko et al., 2021).

Counterfactual probabilities of default holding either the asset value or volatility constant at pre-Paris estimates are displayed in the same plot. When we shut down the volatility channel by holding it constant, there is almost no change in the probability of default. However, there is almost no change in the probability of default when holding volatilities constant, indicating the change in the probability of default is almost entirely captured by the change in asset volatilities. These estimates provide evidence that the change in default probabilities following the Paris Agreement were primarily driven by the change in asset volatilities. These findings show that changes in volatility can actually result in increases in probability of defaults, which presents financial stability ramifications.

Finally, we consider the cross-sectional variations in the changes of asset values and volatilities and whether they are related to regulatory risk. To examine this, we run the following regressions:

$$\Delta V_i^1 = \beta_1 EnvProf_j + \beta_2 HighReg_j + \beta_3 EnvProf_J \times HighReg_j + \kappa_p + \epsilon_i, \tag{29}$$

$$\Delta \sigma_i^1 = \beta_1 EnvProf_j + \beta_2 HighReg_j + \beta_3 EnvProf_J \times HighReg_j + \kappa_p + \epsilon_i, \tag{30}$$

where $\Delta V_t^1, \Delta\sigma_t^1$ are one-month changes in asset values and volatilities, and $HighReg_j$ are high regulatory enforcement firms. In this regression, the main parameter of interest is β_3, which is informative of how asset values and volatilities changed in the month after the Paris Agreement for firms with poor environmental profiles operating in strict regulatory environments. If the change in asset values and volatilities after the Paris Agreement was primarily driven by a change in regulatory risk, we expect that this coefficient should be negative in the asset value regressions and positive in the asset volatility regressions.

Results examining the change in asset values are displayed in the first four columns of Table 10. The results show no statistically significant difference in change in asset values for environmentally problematic firms in high versus low regulatory environments. However, when we examine the changes in asset volatilities for environmentally problematic firms in columns (5) through (8), we find that regulatory enforcement stringency is an important factor. In particular, when we define environmentally problematic firms as those with top-quartile carbon emissions (column 1), we find that these firms that are located in low regulatory enforcement environment experienced a 3.6 percentage point increase in asset volatilities, while the firms located in high regulatory enforcement states experienced a 15.9 $(12.3 + 3.6)$ percentage point increase in asset volatilities. Although the asset values do not appear to be affected by the interaction between an issuer's environmental profile and regulatory exposure, the change in asset volatilities following the Paris Agreement seems to primarily be driven by regulatory risk. The findings on the interaction between a bond's environmental profile and its regulatory exposure imply that firms may be primarily affected by this interaction through the channel of asset volatility.

5.4.1. Policy implications from the changes in default probabilities

Our results suggest important policy implications. In particular, although the model-implied default probabilities eventually reverted back after the period immediately following the Paris Agreement, temporary dislocation of the bond market can have economically material effects on firm investments and ultimately, financial stability and the real economy. For companies whose bonds are affected by the prospective changes in climate regulations, there is a worry that increasing credit spreads could lead to reduced investment, resulting in negative consequences for the real economy (Gilchrist et al., 2014).

At the same time, given the relative illiquidity in the corporate bond market, especially in the high-yield segment, there is worry that disruption in the credit conditions of a number of industries would transmit to other parts of the market and generate credit risk contagion. When credit spreads widen abruptly, they can trigger a sell-off as investors seek to offload perceived risky assets. In an illiquid market, this can exacerbate price declines, leading to a cascading effect that affects even companies not directly related to high-carbon emissions. Policymakers may need to consider mechanisms to enhance liquidity or provide temporary support in times of stress to prevent systemic risks, as evidenced in the recent Covid-19 corporate bond market stress research (O'Hara and Zhou, 2021; Boyarchenko et al., 2021). The possibility that regulators need to provide liquidity in the event of new climate regulation highlights the policy importance of these results.

Another possible source of broader financial stability concern is that in recent years, corporate bonds are largely held by certain types of institutional investors, such as insurers (Koijen and Yogo, 2023). Insurers, banks and other financial institutions that hold corporate bonds of high-carbon-emission companies are directly exposed to any declining value of these assets. A significant drop in bond values can erode the balance sheets of these institutions, thereby impairing their abilities to underwrite insurance, extend credit, and invest in the capital markets. There have been recent proposals for regulators to conduct "climate stress tests" of the financial sector (e.g., Acharya et al., 2023; Jung et al., 2023) and ensure that systemically important institutions have adequate capital buffers and appropriate disclosure about their exposures to high-carbon-emitting sectors. Financial institutions themselves may also mitigate their exposure to high-emitting firms in response to changes in climate policies (e.g., Ivanov et al., 2023).

6. Changes in institutional investor bond ownership around the Paris Agreement

The bond pricing results suggest that after the Paris Agreement, investors reevaluated their corporate bond holdings more exposed to climate risk. A number of recent theory papers argue that green and brown investors view their investments from different perspectives (e.g., Heinkel, Kraus, and Zechner, 2001; Pastor, Stambaugh, and Taylor, 2021; Oehmke and Opp, 2023; Pedersen, Fitzgibbons, and Pomorski, 2021; Goldstein, Kopytov, Lin, and Xiang, 2022). In addition, empirical work shows relationships between certain types of institutional investors and their CSR or carbon risk equity portfolio holdings (Dyck, Lins, Roth, and Wagner, 2019; Ilhan, Krueger, Sautner, and Starks, 2023). Further, Starks, Venkat, and Zhu (2022) provide evidence that institutional investors with longer-term horizons have stronger preferences to invest in firms with higher ESG profiles.

An implication of our analyses on the changes in credit ratings and yield spreads is that investors with varying time horizons could treat the Paris Agreement shock quite differently. That is, investors with longer time horizons may be more concerned with the future changes. Accordingly, we distinguish two classes of major investors in the corporate bond market that have been argued to have different investment horizons: insurance companies and mutual funds due to the differences in their investment strategies. In particular, insurance companies tend to hold their bonds to maturity, while mutual funds tend to trade more frequently and hence have a much shorter horizon (Massa, Yasuda, and Zhang, 2013). As long-term investors have been shown to care more about firms' environmental profiles (Starks, Venkat, and Zhu, 2022), we posit that insurance companies are more likely to reduce their holdings of corporate bonds issued by firms with poor environmental profiles after the Paris Agreement. Further, these changes should be relevant to the bond pricing changes we find because insurance companies collectively hold around 25-30% of corporate bonds and mutual funds hold around 15% of outstanding bonds.

We conduct difference-in-differences analyses using eight quarterly snapshots of institutional portfolio holdings around the Paris Agreement (from the fourth quarter of 2014 to the fourth quarter of 2016). The data consists of institutional investor holdings obtained from Refinitiv eMAXX (formerly Lipper eMAXX). Each quarter, we sum up individual bond holdings of (1) all institutional investors included in the eMAXX reporting entities, (2) all mutual funds, and (3) all insurance companies, where we scale each of the investor's bond holdings by the outstanding amount of the particular bond issue. Each treated bond is matched to a control bond using bond characteristics: issue principal size, credit rating, time to maturity and the oil beta of the firm's equity. We then regress the particular institutional ownership variable (all institutional investors, mutual funds or insurance companies) on an indicator variable indicating quarters after the Paris Agreement, an indicator variable indicating issuers with low environmental profiles and the interaction between the two variables:

$$Ownership_{it} = \beta_1 Treated_i \times AfterParis_t + \beta_2 Treated_i + BondControl + \kappa_t + \epsilon_{it}. \tag{31}$$

We define $Treated_i$ bonds in the same four way by assigning an indicator variable equal to one if the issuing firm (i) is in the top-quartile in terms of firm-level total carbon emissions in 2014, (ii) is in the top-quartile in terms of firm-level carbon intensity, (iii) is in a top carbon emissions industry, or (iv) has a below-median environmental score in December 2014. The bond-level control variables ($BondControl$) include issuance amount, years to maturity, and bond credit rating.

Table 11 shows the results of the difference-in-differences analyses for the changes in total institutional investor ownership, mutual fund ownership, and insurance company ownership around the Paris Agreement for the treated bonds. When we define the treated bonds as bonds issued by firms whose carbon emission amount is in the top-quartile, we find that the total institutional ownership of the treated bonds stay relatively unchanged after the Paris Agreement, but the composition of bond owners shifted significantly. Specifically, we find that insurance companies significantly reduce their holdings of high-emission companies' bonds by 1.022 percentage points, relative to their holdings of matched issuers' bonds. In contrast, the ownership of high-emission issuers' bonds by mutual funds, which typically have a relatively shorter investment horizon, increases by 0.741 percentage point around the Paris Agreement.

The other regression results reported in Table 11 are based on alternative definitions of the treated bonds. A consistent pattern emerges: the total institutional ownership either declines (in the case of high-emission industries) or does not change (in the case of top-quartile carbon intensity and low-median environmental score). However, the ownership held by insurance companies consistently decreases by around one percentage point, while the ownership held by mutual funds consistently increases. These analyses suggest that the Paris Agreement resulted in a transfer of ownership from relatively long-term bond investors (insurance companies) to investors with typically shorter horizons (mutual funds), which is consistent with the argument that environmental and climate risks are likely to materialize in the future and investors have different considerations based on their investment horizon.[30]

7. Conclusions

Environmental risks, particularly climate risks, have been receiving more focused attention from both financial market participants and policy makers. In this study, we provide empirical evidence that suggests uncertainty about future regulatory actions can motivate bond market participants to respond to firms' environmental performance, and particularly, changes in firms' exposures to climate risks.

We present empirical results suggesting that having poor environmental performance, including having a more significant carbon footprint, is associated in general with lower credit ratings and higher bond yield spreads, particularly for firms located in states with stricter environmental regulations. We also provide evidence of a causal component to these results by examining bond credit ratings and yield spreads for environmentally poor firms after a shock to their regulatory risk. We find that the December 2015 Paris Agreement appears to have increased the regulatory risk for firms in high emissions industries or that have poor environmental performance in general,

[30] The reduction of insurance company bond ownership of high-emission firms is not driven by the occurrence of bond credit rating downgrades after the Paris Agreement. In untabulated tests, we drop all bonds that experienced a credit rating downgrade during the 12 months following the Paris Agreement. The results for the remaining bonds in the sample remain robust with a significant reduction of insurance company ownership.

resulting in negative consequences. More importantly, these effects on bond ratings and yields are observed to be stronger in states that enforce regulation more strictly, suggesting that they are stronger because potential new regulations were expected to be enforced more strictly. Finally, when examining the results through a structural lens, we find that consistent with regulatory uncertainty affecting bond pricing, the change in bond yield spreads is primarily due to changes in asset volatility.

Our results have important implications for how firms' environmental profiles are related to market participants' assessments of their corporate bonds' risks and values. The results suggest that credit rating analysts and bond investors are concerned with issuers' environmental profiles because of potential regulatory costs. Additionally, given that the change in bond pricing is associated with a quantitatively meaningful increase in issuers' probabilities of default, climate risks and associated regulatory uncertainties may undermine the financing capacity of high carbon issuers. Insofar as these changes in credit spreads can spillover into the real economy, and present financial stability risks, these findings also provide important lessons for policy makers. That is, the results show that the uncertainty about future climate regulation can instill more volatility into asset prices, particularly for debt instruments. This uncertainty can create challenges to modeling the risks for both investors and policymakers. As pointed out by Berg et al. (2023), welfare would be improved if there were more certainty regarding the path of future policy changes.

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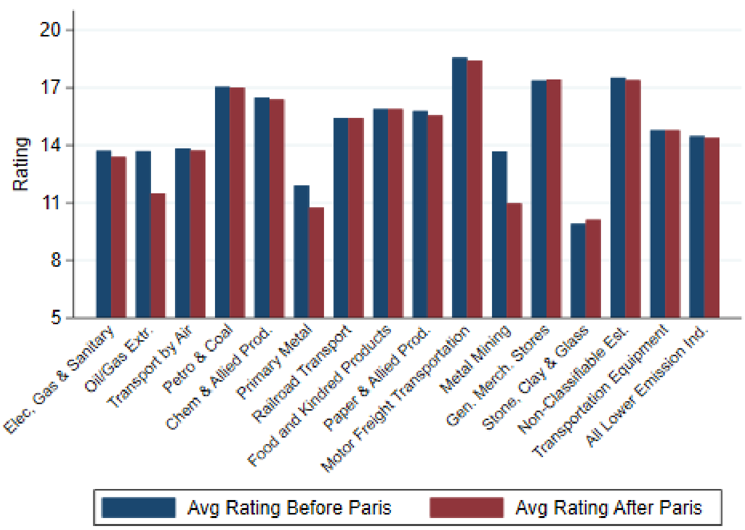
Fig. 1. Credit ratings and yield spreads of high carbon emission industries' bonds before and after the Paris Agreement.
This figure displays equal-weighted average ratings and spreads for each of the top 15 carbon-emitting industries, before and after the Paris Agreement, where the pre-period runs from December 2014 through November 2015 and the post period runs from December 2015 through November 2016. A numerical rating of 1 corresponds to a D rating, a rating of 5 to a Caa2 rating, a rating of 10 to a Ba3 rating, a rating of 15 to a Baa1 rating a rating of 20 to a Aa2 rating and a rating of 22 to a Aaa rating.

(a) Ratings



(b) Spreads

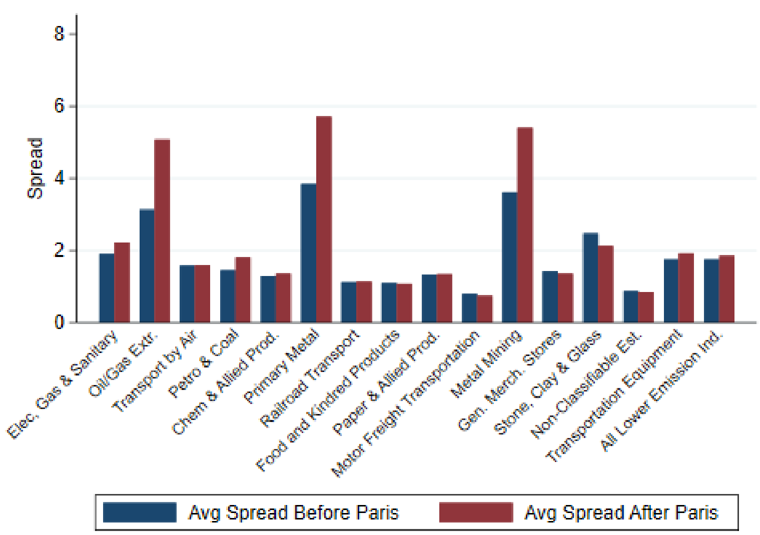
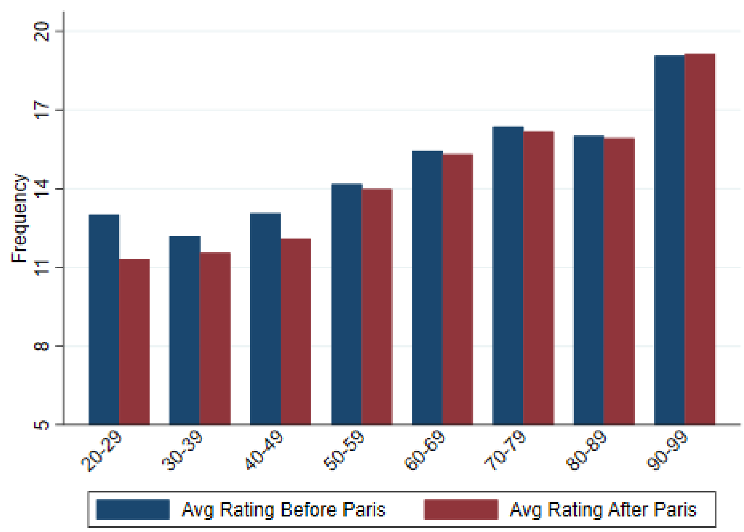


Fig. 2. Ratings and spreads by environmental scores before and after the Paris Agreement. This figure displays equal-weighted average ratings and spreads for firms divided by their levels of Sustainalytics Environmental scores, before and after the Paris Agreement, where the pre-period runs from December 2014 through November 2015 and the post period runs from December 2015 through November 2016. A numerical rating of 1 corresponds to a D rating, a rating of 5 to a Caa2 rating, a rating of 10 to a Ba3 rating, a rating of 15 to a Baa1 rating a rating of 20 to a Aa2 rating and a rating of 22 to a Aaa rating.

(a) Ratings



(b) Spread

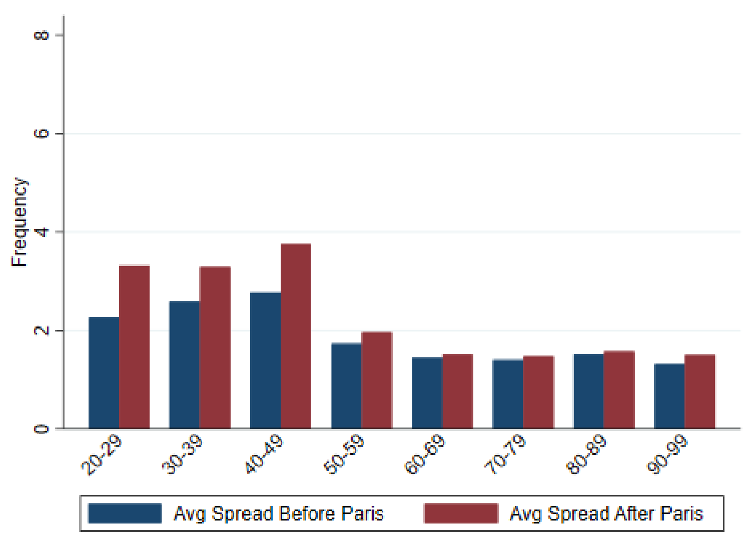


Fig. 3. Bond credit ratings around the Paris Agreement announcement.
This figure plots the coefficients from the following regression equation:
$Rating_{it} = \sum_{k=-11}^{11} \beta_k [\mathbb{1}(t = k) \times EnvProf_j] + \gamma_i + \kappa_t + \epsilon_{it}$.
$EnvProf_j$ is equal to one for treated observations, where the treatment is defined alternatively as a below-median environmental score, being in the top 15 carbon-emitting industries, being in the top-quartile of CDP emissions, or being in the top-quartile of CDP carbon intensity (tons of emissions divided by revenue in $1,000). Control observations are all other securities. γ_i, κ_{tp} are security and time fixed effects. Pre-period runs from December 2014 through November 2015 and post-period runs December 2015 through November 2016. The chart includes all interaction terms except for December 2014, which serves as the benchmark period. Higher numerical scores indicate better credit ratings. We show 90% confidence intervals, where standard errors are double-clustered at the 3-digit SIC industry and month levels.

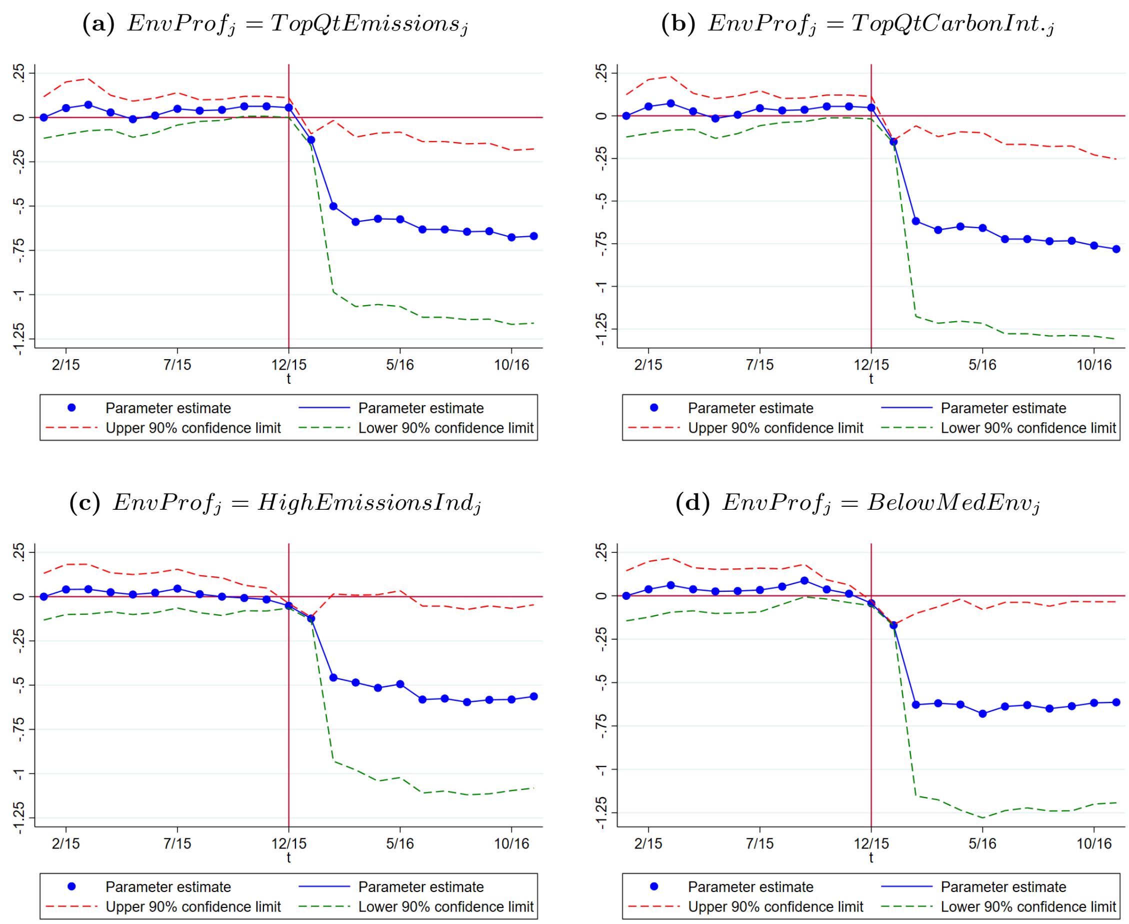
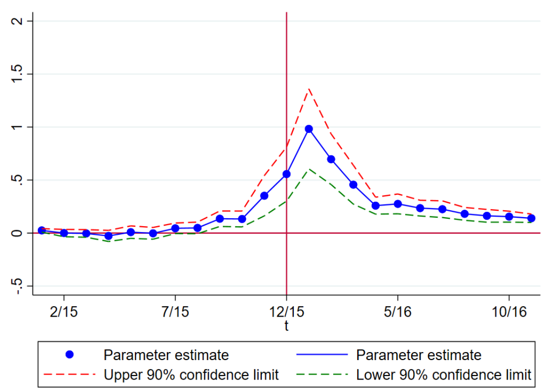
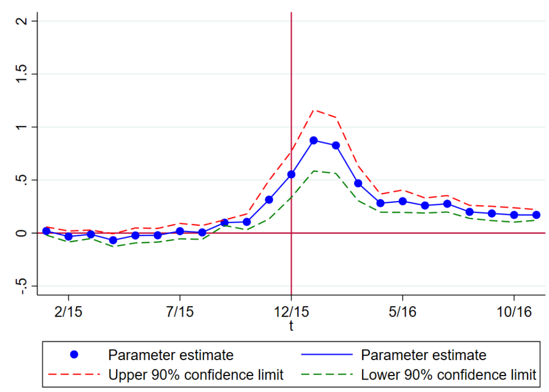


Fig. 4. Yield spreads around the Paris Agreement announcement.
This figure plots the coefficients from the following regression equation:
$Spread_{it} = \sum_{k=-11}^{11} \beta_k[\mathbb{1}(t = k) * EnvProf_j] + \gamma_i + \kappa_{tp} + \epsilon_{it}$.
$EnvProf_j$ is equal to one for treated observations, where the treatment is defined alternatively as a below-median environmental score, being in the top 15 carbon-emitting industries, being in the top-quartile of CDP emissions, or being in the top-quartile of CDP carbon intensity (tons of emissions divided by revenues in $1,000). Control observations are selected using a one-to-one nearest neighbor matching with replacement by Mahalanobis matching with replacement procedure on rating, time to maturity, issue principal outstanding and oil beta as of year-end 2014. γ_i, κ_{tp} are security and matched-pair-by-time fixed effects. Pre-period runs from December 2014 through November 2015 and post-period runs December 2015 through November 2016. The chart includes all interaction terms except for December 2014, which serves as the benchmark period. We show 90% confidence intervals, where standard errors are double-clustered at the 3-digit SIC industry and month levels.

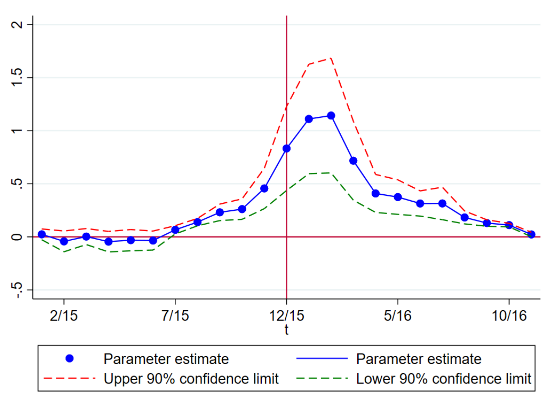
(a) $EnvProf_j = TopQtEmissions_j$



(b) $EnvProf_j = TopQtCarbonInt._j$



(c) $EnvProf_j = HighEmissionsInd_j$



(d) $EnvProf_j = BelowMedEnv_j$

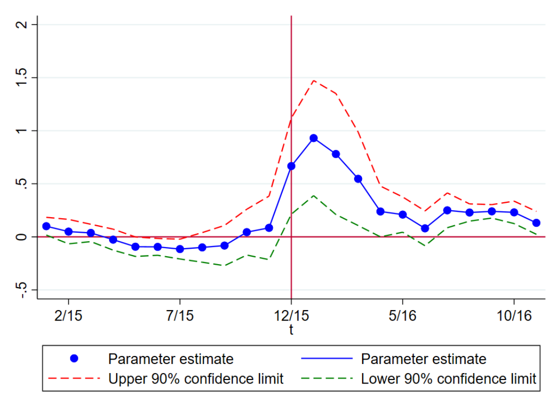
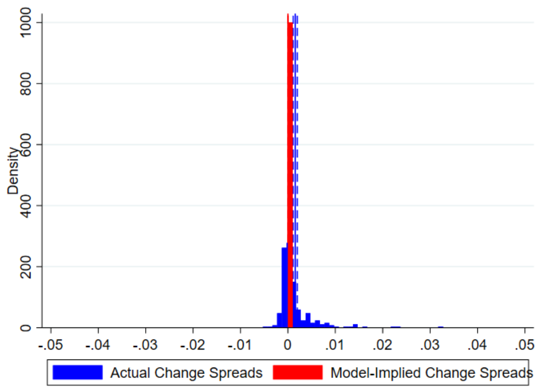
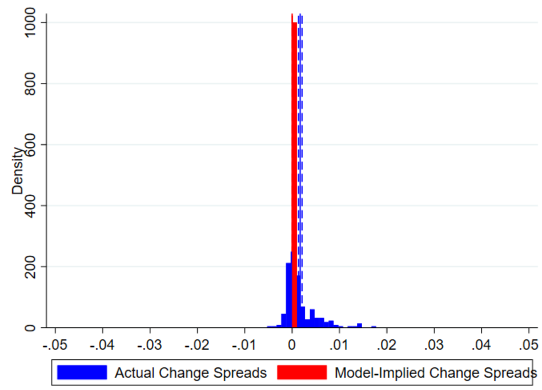


Fig. 5. Changes in model-implied yield spreads around the Paris Agreement announcement
This figure plots the distribution in the observed change in the credit component of spreads relative to the change in the model-implied spread based on asset values and volatilities calculated from Vassalou and Xing (2004) for bonds issued by firms with poor environmental profiles in the month after the Paris Agreement. The model-implied change in spreads assumes a constant asset volatility before and after the Paris Agreement. A poor environmental profile is determined by whether an issuer is in the top-quartile of emissions (Panel a), in the top-quartile of emission-intensity (Panel b), in the top 15 carbon emission industries (Panel c), or has a below-median environmental score (Panel d). The blue-solid line shows the actual average change in yield spreads, while the red-solid line shows the model-implied change in yield spreads. The blue and red dashed lines show the 90% confidence intervals.

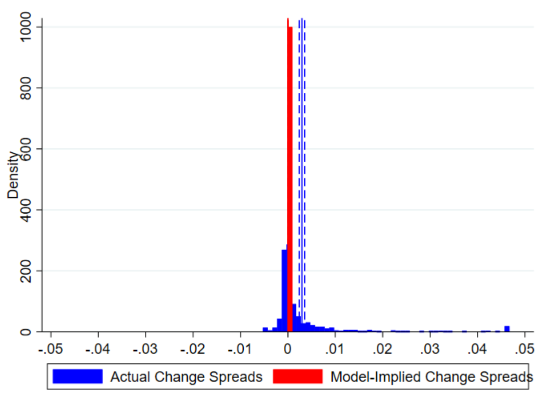
(a) Top Quartile Emissions



(b) Top Quartile Carbon Intensity



(c) Top 15 Emitting Industry



(d) Below Median Environmental Score

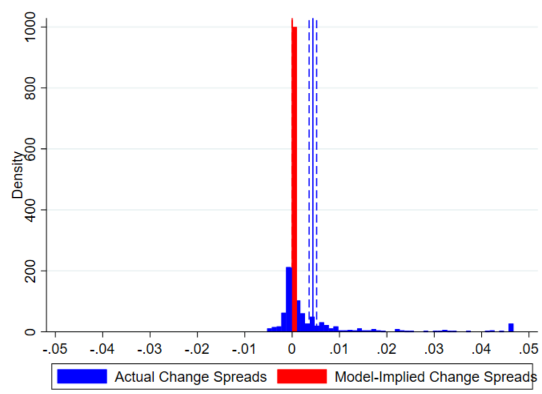
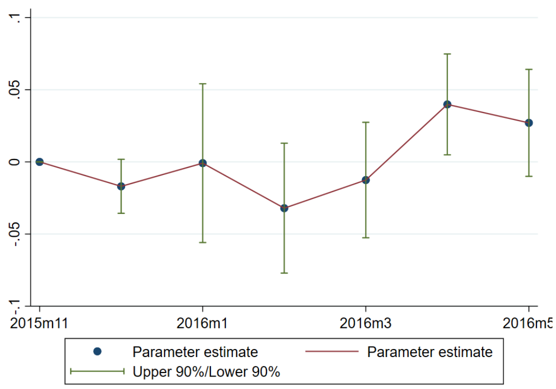


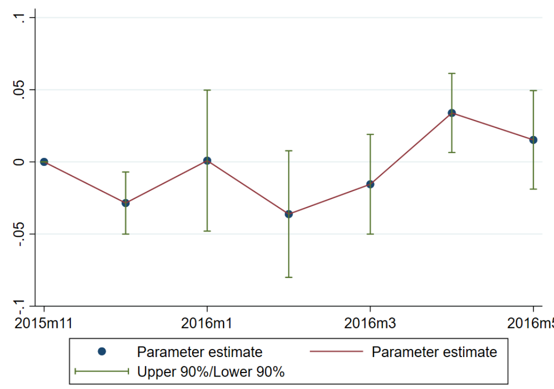
Fig. 6. Changes in asset value around the Paris Agreement announcement

This figure plots period-by-period regressions of the percent change in asset value on an environmentally problematic firm indicator from the month before Paris (2015m11) and the next six months. The indicator is one if an issuer is in the top-quartile of emissions (Panel a), in the top-quartile of emission-intensity (Panel b), in the top 15 carbon emission industries (Panel c), or has a below-median environmental score (Panel d). Control observations are selected using a one-to-one nearest neighbor Mahalanobis matching with replacement procedure on rating, time to maturity, issue principal outstanding and oil beta as of year-end 2014. Standard errors are clustered at the 3-digit SIC industry level.

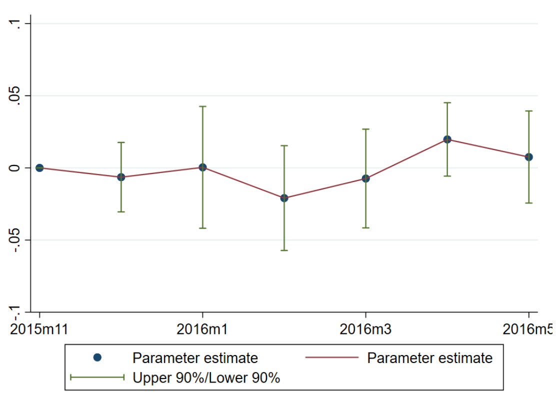
(a) Top Quartile Emissions



(b) Top Quartile Carbon Intensity



(c) Top 15 Emitting Industry



(d) Below Median Environmental Score

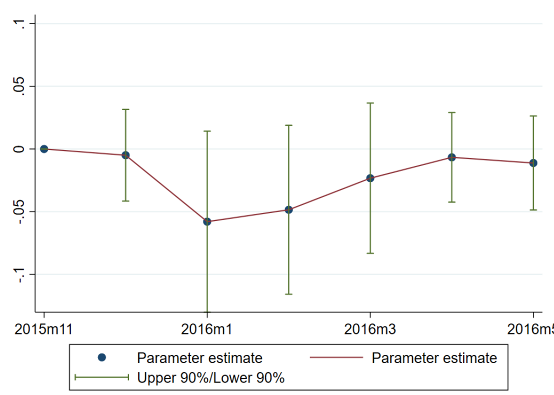
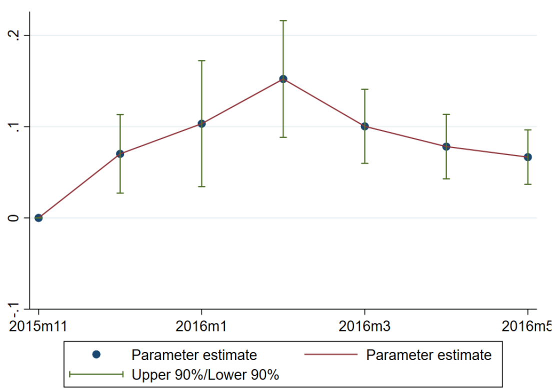
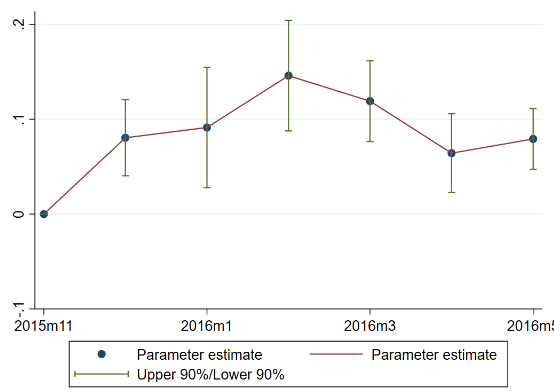


Fig. 7. Changes in asset volatilities around the Paris Agreement announcement
This figure plots period-by-period regressions of the change in asset volatilities on an environmentally problematic firm indicator from the month before Paris (2015m11) and the next six months. The indicator is one if an issuer is in the top-quartile of emissions (Panel a), in the top-quartile of emission-intensity (Panel b), in the top 15 carbon emission industries (Panel c), or has a below-median environmental score (Panel d). Control observations are selected using a one-to-one nearest neighbor Mahalanobis matching with replacement procedure on rating, time to maturity, issue principal outstanding and oil beta as of year-end 2014. Standard errors are clustered at the 3-digit SIC industry level.

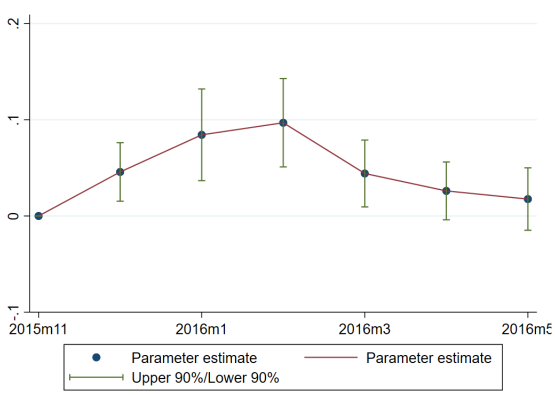
(a) Top Quartile Emissions



(b) Top Quartile Carbon Intensity



(c) Top 15 Emitting Industry



(d) Below Median Environmental Score

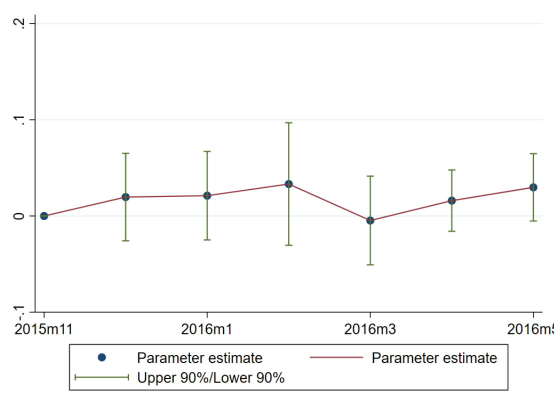


Fig. 8. Changes in high emissions firms' default probability relative to counterfactuals
The blue line plots the change in the probability of default for high emissions issuers estimated using a Merton model based on the estimated asset value and volatilites solved from observed credit spread changes and equity returns. The red line and the green line plot the counterfactual probability of default where the high emissions issuers' asset value or asset volatilities are held constant at their pre-Paris level, respectively. High emissions firms are defined as firms in the top quartile of carbon emissions. The calculations are based on a one-year time horizon.

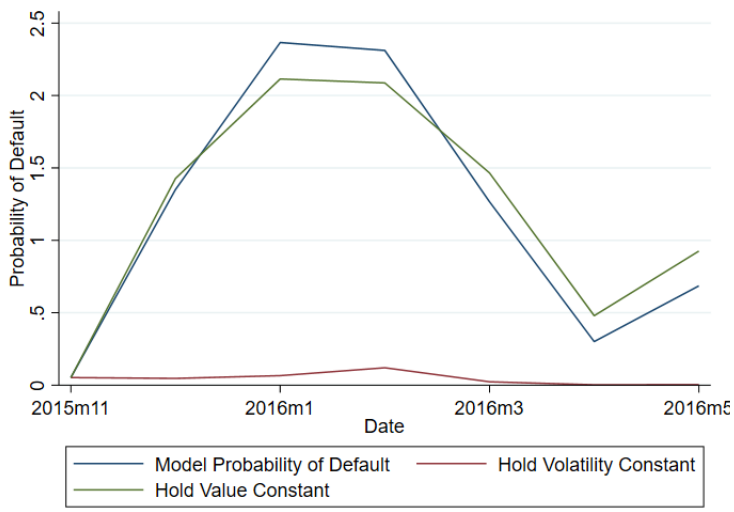


Table 1: Summary statistics.

This table reports the summary statistics for the at issue bond sample with a sample period of 2009 through 2017. Trading yield spread, yield, profitability, leverage, annual returns, ln(total assets), and cash/assets are winsorized at the 1% and 99% levels. The ratings variable is assigned such that a higher number indicates a better rating. A numerical rating of 1 corresponds to a D rating, a rating of 5 to a Caa2 rating, a rating of 10 to a Ba3 rating, a rating of 15 to a Baa1 rating a rating of 20 to a Aa2 rating and a rating of 22 to a Aaa rating. Reg stringency is measured as the firm's regulatory stringency determined as the revenue-weighted average number of EPA penalties issued in a given year divided by the number of facilities (in thousands) in that state for the states the firm operates in. When information on a firm's facility locations is not available, the number of EPA penalties in the state the firm's headquarters are located in divided by the number of plants regulated by the EPA in that state (in thousands). Top 15 emissions industries are defined as the top 15 carbon emissions industries based on carbon emissions using the CDP data.

Variable	Observations	Mean	Median	Std. Dev.
Credit rating	1,940	15.312	15.000	2.828
Offering spread	1,940	1.835	1.481	1.273
Firm-weighted average maturity	1,940	9.414	9.274	3.336
Environmental score	1,940	59.960	60.000	14.050
Reg Stringency	1,940	0.714	0.446	0.950
Top 15 emissions industry	1,940	0.487	0.000	0.500
Emissions (millions of ton)	1,312	6.680	0.438	19.665
Carbon intensity (ton per $1,000 revenue)	1,312	0.319	0.014	0.997
Ln(1 + Principal)	1,940	13.384	13.305	0.602
Time to maturity	1,940	9.969	10.000	7.289
Callable	1,940	0.970	1.000	0.170
Leverage	1,940	0.287	0.274	0.147
Pre-tax interest coverage	1,940	19.303	11.760	23.433
Ln(Total assets)	1,940	10.197	10.234	1.259
Cash/assets	1,940	0.118	0.072	0.131
Profitability	1,940	0.222	0.168	0.185
Tangibility	1,940	0.302	0.188	0.256
Annual stock returns	1,940	15.599	13.648	24.203
Ln(Standard deviation of returns)	1,940	2.939	2.902	0.415

Table 2: Credit ratings and regulatory stringency

This table displays results from the following panel regression:

$$Rating_{it} = \beta_1 EnvProf_{jt-1} + \beta_2 Reg_{jt-1} + \beta_3 EnvProf_{jt-1} \times Reg_{jt-1} + \beta_4 X_{jt-1} + FE + \epsilon_{it}.$$

All observations are at-issue bonds. Environmental scores, leverage, ln(total assets), profitability, annual stock returns, and the standard deviation of stock returns are winsorized at the 1% and 99% levels and are measured at the end of the previous year. Reg stringency, defined as the revenue-weighted average number of EPA penalties in a given year divided by the number of facilities in that state (for the states in which the firm operates), is also standardized by mean and scaled by standard deviation. *, ** and *** indicate 10%, 5% and 1% significance, respectively. Fixed effects are indicated in each column. Standard errors, which are double-clustered at the 3-digit SIC industry and month levels, are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Environmental Score × Reg Stringency	0.020***			0.019***		
	(0.007)			(0.005)		
Emissions × Reg Stringency		-0.021**			-0.021***	
		(0.009)			(0.008)	
Carbon Intensity × Reg Stringency			-0.283**			-0.328***
			(0.112)			(0.099)
Environmental Score	0.027***			0.014**		
	(0.009)			(0.007)		
Emissions		-0.013			-0.014**	
		(0.010)			(0.006)	
Carbon Intensity			-0.514***			-0.231***
			(0.138)			(0.070)
Reg Stringency	-1.031***	0.180*	0.140	-0.983***	0.127	0.114
	(0.336)	(0.102)	(0.101)	(0.271)	(0.087)	(0.087)
Firm Weighted Average Maturity	0.016	-0.026	-0.035	0.041	-0.004	-0.003
	(0.032)	(0.034)	(0.037)	(0.027)	(0.031)	(0.032)
Leverage	-1.978*	-0.394	-0.221	-2.146**	-1.312	-1.299
	(1.093)	(1.299)	(1.250)	(1.074)	(1.280)	(1.295)
Pre-tax interest coverage	0.029***	0.037***	0.035***	0.021***	0.017***	0.016***
	(0.006)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)
Ln(Total Assets)	0.946***	1.085***	1.033***	1.059***	1.201***	1.191***
	(0.157)	(0.171)	(0.169)	(0.152)	(0.150)	(0.148)
Cash/Assets	3.904***	5.178***	5.324***	2.501**	3.099***	3.163***
	(1.069)	(1.181)	(1.195)	(1.099)	(0.946)	(0.946)
Profitability	0.776	1.187	0.688	0.442	3.716**	3.647**
	(0.826)	(0.958)	(0.905)	(1.054)	(1.438)	(1.416)
Tangibility	-0.258	0.496	1.100*	1.679*	1.991	2.006
	(0.500)	(0.543)	(0.608)	(1.000)	(1.346)	(1.351)
Annual Stock Returns	-0.006**	-0.005	-0.004	-0.005**	-0.001	-0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Ln(Standard Deviation Returns)	-1.785***	-1.957***	-2.100***	-1.665***	-1.533***	-1.533***
	(0.267)	(0.339)	(0.318)	(0.231)	(0.245)	(0.244)
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	N	N	N	Y	Y	Y
Within R2	0.587	0.555	0.574	0.546	0.526	0.527
Observations	1,940	1,312	1,312	1,938	1,309	1,309

Table 3: Offering spreads and regulatory stringency.

This table displays results from the following panel regression:

$$Spread_{it} = \beta_1 EnvProf_{jt-1} + \beta_2 Reg_{jt-1} + \beta_3 EnvProf_{jt-1} \times Reg_{jt-1} + \beta_4 X_{jt-1} + \beta_5 Z_{it} + FE + \epsilon_{it}.$$

All observations are at-issue bonds. Environmental scores, coupon rate, leverage, ln(total assets), profitability, annual stock returns, and the standard deviation of stock returns are winsorized at the 1% and 99% levels. Firm characteristics are measured as of the end of the previous year. Reg stringency, defined as the revenue-weighted average number of EPA penalties in a given year divided by the number of facilities in that state (for the states in which the firm has facilities), is also standardized by mean and scaled by standard deviation. *, ** and *** indicate 10%, 5% and 1% significance, respectively. Fixed effects are indicated in each column. Standard errors, which are double-clustered at the 3-digit SIC industry and month levels, are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Environmental Score × Reg Stringency	-0.005**			-0.006***		
	(0.002)			(0.002)		
Emissions × Reg Stringency		0.007**			0.009***	
		(0.004)			(0.003)	
Carbon Intensity × Reg Stringency			0.073			0.101
			(0.068)			(0.063)
Environmental Score	-0.009***			-0.004		
	(0.003)			(0.003)		
Emissions		0.007***			0.003	
		(0.002)			(0.002)	
Carbon Intensity			0.162***			0.088**
			(0.053)			(0.044)
Reg Stringency	0.225**	-0.078**	-0.065*	0.333***	-0.062**	-0.054**
	(0.112)	(0.037)	(0.035)	(0.101)	(0.027)	(0.026)
Ln(1 + Principal)	0.254***	0.189***	0.216***	0.217***	0.179***	0.184***
	(0.069)	(0.062)	(0.062)	(0.050)	(0.049)	(0.049)
Time to Maturity	0.090***	0.093***	0.093***	0.091***	0.094***	0.094***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Callable	0.391**	0.296**	0.275**	0.058	0.033	0.022
	(0.190)	(0.129)	(0.128)	(0.112)	(0.123)	(0.127)
Leverage	1.193**	0.520	0.435	1.004**	0.582	0.586
	(0.458)	(0.438)	(0.424)	(0.411)	(0.411)	(0.415)
Pre-tax interest coverage	-0.007***	-0.007***	-0.006***	-0.006***	-0.005***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Total Assets)	-0.250***	-0.190***	-0.177***	-0.297***	-0.236***	-0.237***
	(0.047)	(0.038)	(0.037)	(0.060)	(0.050)	(0.050)
Cash/Assets	-0.473	-0.564**	-0.635**	-0.184	-0.361	-0.368
	(0.305)	(0.266)	(0.260)	(0.257)	(0.285)	(0.295)
Profitability	-0.246	-0.211	-0.081	-0.322	-0.715	-0.685
	(0.250)	(0.181)	(0.175)	(0.444)	(0.564)	(0.563)
Tangibility	0.157	-0.291*	-0.366**	0.197	-0.530	-0.561*
	(0.156)	(0.167)	(0.153)	(0.348)	(0.330)	(0.331)
Annual Stock Returns	-0.003**	-0.003**	-0.003**	-0.003**	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Standard Deviation Returns)	1.045***	0.850***	0.878***	0.927***	0.675***	0.677***
	(0.113)	(0.125)	(0.123)	(0.115)	(0.125)	(0.124)
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	N	N	N	Y	Y	Y
Within R2	0.596	0.672	0.678	0.601	0.715	0.715
Observations	1,940	1,312	1,312	1,938	1,309	1,309

Table 4: Effects of the Paris Agreement on credit ratings.

This table displays results from the following regression:

$$Rating_{it} = \beta_1 EnvProf_j \times AfterParis_t + \gamma_i + \kappa_t + \epsilon_{it}$$

$Env.Prof_j$ is alternatively one of the following: an indicator variable equal to one if the firm is in the top quartile of carbon emissions in 2014 (*Top Quartile Emissions*), an indicator variable equal to one if the firm is in the top quartile of carbon intensity (defined as tons of emissions per $1,000 in revenue) in 2014 (*Top Quartile Carbon Intensity*), an indicator variable equal to one if the firm is in one of the top 15 carbon-emitting industries (*High Emission Industry*), or an indicator variable equal to one if the firm a below median environmental score in December 2014 (*Low Environmental Score*). $AfterParis_t$ is an indicator variable equal to one if the observation occurs in December 2015 or later. γ_i, κ_t are security and time fixed effects. Sample runs from December 2014 through November 2016. *, ** and *** indicate 10%, 5% and 1% significance, respectively. Standard errors, which are double-clustered at the 3-digit SIC industry and month levels, are shown in parentheses.

	(1)	(2)	(3)	(4)
After Paris × Top-Quartile Emissions	-0.551*			
	(0.272)			
After Paris × Top-Quartile Carbon Intensity		-0.627*		
		(0.304)		
After Paris × High Emissions Industry			-0.482	
			(0.285)	
After Paris × Low Environmental Score				-0.580*
				(0.321)
Time Fixed Effects	Y	Y	Y	Y
Security Fixed Effects	Y	Y	Y	Y
Within R2	0.068	0.083	0.040	0.052
Observations	23,184	23,184	33,336	33,336

Table 5: Effects of the Paris Agreement on yield spreads.

This table displays results from the following regression:

$$Spread_{it} = \beta_1 EnvProf_j \times AfterParis_t + \gamma_i + \kappa_{tp} + \epsilon_{it}$$

$Env.Prof_j$ is alternatively one of the following: an indicator variable equal to one if the firm is in the top quartile of carbon emissions in 2014 (*Top Quartile Emissions*), an indicator variable equal to one if the firm is in the top quartile of carbon intensity (defined as tons of emissions per $1,000 in revenue) in 2014 (*Top Quartile Carbon Intensity*), an indicator variable equal to one if the firm is in one of the top 15 carbon-emitting industries (*High Emission Industry*), or an indicator variable equal to one if the firm a below median environmental score in December 2014 (*Low Environmental Score*). $AfterParis_t$ is an indicator variable equal to one if the observation occurs in December 2015 or later. γ_i, κ_{tp} are security and matched-pair-by-time fixed effects. The sample is formed by using one-to-one nearest neighbor Mahalanobis matching of treated bond issues to control bond issues by oil beta, issue principal outstanding, time to maturity and credit rating as of year-end 2014. The sample period includes observations from December 2014 through November 2016. *, ** and *** indicate 10%, 5% and 1% significance, respectively. Standard errors, which are double-clustered at the 3-digit SIC industry and month levels, are shown in parentheses.

	(1)	(2)	(3)	(4)
After Paris × Top-Quartile Emissions	0.301***			
	(0.105)			
After Paris × Top-Quartile Carbon Intensity		0.347***		
		(0.107)		
After Paris × High Emissions Industry			0.386**	
			(0.167)	
After Paris × Low Environmental Score				0.394***
				(0.140)
Pair-Time Fixed Effects	Y	Y	Y	Y
Security Fixed Effects	Y	Y	Y	Y
Within R2	0.029	0.051	0.023	0.015
Observations	12,096	10,416	31,008	21,504

Table 6: Regulatory stringency and the effects of the Paris Agreement on credit ratings.

This table displays results from the following regression:

$$Rating_{it} = \gamma_i + \kappa_t + \beta_1 AfterParis_t \times EnvProf_j + \beta_2 AfterParis_t \times HighReg_j + \beta_3 EnvProf_j \times HighReg_j + \beta_4 AfterParis_t \times EnvProf_j \times HighReg_j + \gamma_i + \kappa_t + \epsilon_{it}.$$

$Env.Prof_j$ is alternatively one of the following: an indicator variable equal to one if the firm is in the top quartile of carbon emissions in 2014 (*Top Quartile Emissions*), an indicator variable equal to one if the firm is in the top quartile of carbon intensity (defined as tons of emissions per $1,000 in revenue) in 2014 (*Top Quartile Carbon Intensity*), an indicator variable equal to one if the firm is in one of the top 15 carbon-emitting industries (*High Emission Industry*), or an indicator variable equal to one if the firm a below median environmental score in December 2014 (*Low Environmental Score*). $AfterParis_t$ is an indicator variable equal to one if the observation occurs in December 2015 or later. $HighReg_j$ is equal to one if the firm is in the top-quartile of exposure to EPA penalties from 2012 through 2015. γ_i, κ_t are security and time fixed effects. Sample is from December 2014 until November 2016. *, ** and *** indicate 10%, 5% and 1% significance, respectively. Standard errors, which are double-clustered at the 3-digit SIC industry and month levels, are shown in parentheses.

	(1)	(2)	(3)	(4)
After Paris × Top-Quartile Emissions × High Reg	-1.371***			
	(0.414)			
After Paris × Top-Quartile Carbon Intensity × High Reg		-1.385***		
		(0.383)		
After Paris × High Emissions Industry × High Reg			-1.094**	
			(0.462)	
After Paris × Low Environmental Score × High Reg				-0.990**
				(0.449)
After Paris × Top-Quartile Emissions	-0.153			
	(0.098)			
After Paris × Top-Quartile Carbon Intensity		-0.157		
		(0.100)		
After Paris × High Emissions Industry			-0.111	
			(0.091)	
After Paris × Low Environmental Score				-0.100
				(0.114)
After Paris × High Reg	0.037	0.112	-0.009	-0.121
	(0.133)	(0.115)	(0.145)	(0.146)
Time Fixed Effects	Y	Y	Y	Y
Security Fixed Effects	Y	Y	Y	Y
Within R2	0.182	0.189	0.134	0.126
Observations	23,184	23,184	33,336	33,336

Table 7: Regulatory stringency and effects of the Paris Agreement on yield spreads.

This table displays results from the following regression:

$$Spread_{it} = \gamma_i + \kappa_{tp} + \beta_1 AfterParis_t \times EnvProf_j + \beta_2 AfterParis_t \times HighReg_j$$
$$+ \beta_3 EnvProf_j \times HighReg_j + \beta_4 AfterParis_t \times EnvProf_j \times HighReg_j + \gamma_i + \kappa_{tp} + \epsilon_{it}.$$

$Env.Prof_j$ is alternatively one of the following: an indicator variable equal to one if the firm is in the top quartile of carbon emissions in 2014 (*Top Quartile Emissions*), an indicator variable equal to one if the firm is in the top quartile of carbon intensity (defined as tons of emissions per $1,000 in revenue) in 2014 (*Top Quartile Carbon Intensity*), an indicator variable equal to one if the firm is in one of the top 15 carbon-emitting industries (*High Emission Industry*), or an indicator variable equal to one if the firm a below median environmental score in December 2014 (*Low Environmental Score*). $AfterParis_t$ is an indicator variable equal to one if the observation occurs in December 2015 or later. $HighReg_j$ is equal to one if the firm is in the top-quartile of exposure to EPA penalties from 2012 through 2015. γ_i, κ_{tp} are security and matched-pair-by-time fixed effects. The sample is formed by using one-to-one nearest neighbor Mahalanobis matching of treated bond issues to control bond issues by oil beta, issue principal outstanding, time to maturity, and credit rating as of year-end 2014. The sample period runs from December 2014 until November 2016. *, ** and *** indicate 10%, 5% and 1% significance respectively. Standard errors, which are double-clustered at the 3-digit SIC industry and month levels, are shown in parentheses.

	(1)	(2)	(3)	(4)
After Paris × Top-Quartile Emissions × High Reg	0.199			
	(0.225)			
After Paris × Top-Quartile Carbon Intensity × High Reg		0.264		
		(0.176)		
After Paris × High Emissions Industry × High Reg			0.700*	
			(0.356)	
After Paris × Low Environmental Score × High Reg				0.911**
				(0.386)
After Paris × Top-Quartile Emissions	0.181**			
	(0.081)			
After Paris × Top-Quartile Carbon Intensity		0.227**		
		(0.096)		
After Paris × High Emissions Industry			0.146**	
			(0.068)	
After Paris × Low Environmental Score				0.033
				(0.078)
After Paris × High Reg	0.340*	0.125	0.083	-0.169
	(0.185)	(0.106)	(0.115)	(0.179)
Pair-Time Fixed Effects	Y	Y	Y	Y
Security Fixed Effects	Y	Y	Y	Y
Within R2	0.050	0.066	0.044	0.029
Observations	12,096	10,416	31,008	21,504

Table 8: Effects of the Paris Agreement on asset value and volatilities

This table displays results of a regression of the percent change in asset values and volatilities observed over different time horizons on a poor environmental indicator. The indicator equals one if an issuer is in the top-quartile of emissions, in the top-quartile of emission-intensity, in the top 15 carbon emission industries, or has a below-median environmental score. Control observations are selected using a one-to-one nearest neighbor Mahalanobis matching with replacement procedure on rating, time to maturity, issue principal outstanding, and oil beta as of year-end 2014. *, ** and *** indicate 10%, 5% and 1% significance, respectively. Standard errors, which are clustered at the 3-digit SIC industry level, are shown in parentheses.

Dependent Variable	Asset Value				Asset Volatilities			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A – 1 month								
Top-Quartile Emissions	-0.017				0.070**			
	(0.011)				(0.026)			
Top-Quartile Carbon Intensity		-0.029**				0.081***		
		(0.013)				(0.024)		
High Emissions Industry			-0.006				0.046**	
			(0.015)				(0.019)	
Low Environmental Score				-0.005				0.020
				(0.022)				(0.028)
Pair Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Panel B – 3 months								
Top-Quartile Emissions	-0.032				0.152***			
	(0.027)				(0.039)			
Top-Quartile Carbon Intensity		-0.036				0.146***		
		(0.027)				(0.036)		
High Emissions Industry			-0.021				0.097***	
			(0.022)				(0.028)	
Low Environmental Score				-0.048				0.033
				(0.041)				(0.039)
Pair Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Panel C – 6 months								
Top-Quartile Emissions	0.027				0.067***			
	(0.023)				(0.018)			
Top-Quartile Carbon Intensity		0.015				0.079***		
		(0.021)				(0.020)		
High Emissions Industry			0.008				0.018	
			(0.019)				(0.020)	
Low Environmental Score				-0.011				0.030
				(0.023)				(0.021)
Pair Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y

Table 9: Change in high emissions firms' probabilities of default

These figures show how probabilities of default (estimated from a Merton model) changed for bonds issued by firms in the top-quartile of carbon emissions relative to matched control issuers in the three months after the Paris Agreement. Probabilities of default are estimated using a one year horizon. Matched controls are chosen in the same way as in the difference-in-differences analysis on bond yield spreads. Probabilities of default are winsorized at the 5% and 95% levels.

	Pre-Paris	3 Months After Paris	Difference
Panel A – All Bonds			
Top-Quartile Emissions	0.04	2.08	2.04*
Matched Control	0.03	0.24	0.21
Difference	0.00	1.84**	1.84**
Panel B – Investment Grade Bonds			
Top-Quartile Emissions	0.02	1.08	1.06**
Matched Control	0.03	0.24	0.22
Difference	0.00	0.83***	0.84***
Panel C – Noninvestment Grade Bonds			
Top-Quartile Emissions	0.24	8.49	8.25**
Matched Control	0.08	0.07	-0.01
Difference	0.16	8.42**	8.26**

Table 10: Regulatory stringency and the effects of the Paris Agreement on asset value and volatilities

This table displays results of a regression of the percent change in asset value and volatilities observed in the month after the Paris Agreement on poor environmental indicators interacted with a regulatory stringency indicator. The poor environmental indicator equals one if an issuer is in the top-quartile of emissions, in the top-quartile of emission-intensity, in the top 15 carbon emission industries, or has a below-median environmental score. Bonds are identified as operating in high regulatory stringency environments if the issuing firm has top-quartile exposure to EPA penalties from 2012 through 2015. Control observations are selected using a one-to-one nearest neighbor Mahalanobis matching with replacement procedure on rating, time to maturity, issue principal outstanding and oil beta as of year-end 2014. *, ** and *** indicate 10%, 5% and 1% significance, respectively. Standard errors, which are clustered at the 3-digit SIC industry level, are shown in parentheses.

Dependent Variable	Asset Value				Asset Volatilities			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top-Quartile Emissions × High Reg	-0.039*				0.123**			
	(0.023)				(0.054)			
Top-Quartile Carbon Intensity × High Reg		-0.031				0.148**		
		(0.031)				(0.059)		
High Emissions Industry × High Reg			-0.013				0.086*	
			(0.029)				(0.049)	
Low Environmental Score × High Reg				0.029				0.062
				(0.052)				(0.042)
Top-Quartile Emissions	-0.005				0.036*			
	(0.013)				(0.021)			
Top-Quartile Carbon Intensity		-0.012				0.040*		
		(0.014)				(0.023)		
High Emissions Industry			0.007				0.011	
			(0.012)				(0.017)	
Low Environmental Score				0.001				-0.024
				(0.021)				(0.018)
High Reg	0.009	-0.016	-0.033	-0.079*	-0.038	-0.056*	0.003	0.063
	(0.017)	(0.026)	(0.022)	(0.043)	(0.041)	(0.032)	(0.043)	(0.048)
Pair Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y

Table 11: Changes in institutional investor bond ownership around the Paris Agreement.

This table reports changes in institutional investor ownership of corporate bonds around the signing of the Paris Agreement. Quarterly observations cover the fourth quarter of 2014 through the fourth quarter of 2016. The periods after the fourth quarter of 2015 constitute the *Post Paris Agreement* periods. Treated bonds are defined in four ways: (1) the issuer company has a top-quartile carbon emission level as of 2014 (per CDP disclosure), (2) the issuer company has a top-quartile carbon intensity (carbon emissions scaled by revenues) as of 2014, (3) the issuer company belongs to a high emissions industry (one of the top 15 most carbon-emitting industries), or (4) the issuer company has a below-median Sustainalytics environmental score as of December 2014, . Control bonds are one-to-one matched to treated bonds based on issue principal size, credit rating, bond time to maturity and the firm's equity oil beta. Standard errors are two-way clustered at the bond and quarter level and shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Treated bond defined by:	Top-quartile firm carbon emission			Top-quartile firm carbon intensity		
Ownership (%) by	All institutions	Mutual funds	Insurance firms	All institutions	Mutual funds	Insurance firms
	(1)	(2)	(3)	(4)	(5)	(6)
Treated bonds * Post Paris Agreement	-0.278	0.741***	-1.022***	-0.308	0.883***	-1.230**
	(0.221)	(0.163)	(0.233)	(0.378)	(0.165)	(0.398)
Treated bonds	2.218	0.137	2.060	1.618	0.431	1.192
	(1.584)	(1.110)	(1.849)	(1.477)	(1.232)	(1.861)
Ln(Issue amount)	-8.282***	0.813	-9.118***	-6.491***	0.535	-7.045***
	(1.369)	(0.869)	(1.579)	(1.740)	(0.990)	(1.995)
Years to maturity	-0.100	-0.204***	0.114	-0.0929	-0.187***	0.103
	(0.0903)	(0.0376)	(0.0968)	(0.0924)	(0.0365)	(0.101)
Credit rating (numerical)	0.131	-0.444**	0.571**	0.235	-0.549**	0.780**
	(0.218)	(0.139)	(0.240)	(0.190)	(0.201)	(0.258)
Observations	4375	4375	4375	3742	3742	3742
Adjusted R^2	0.110	0.113	0.105	0.088	0.110	0.093
Time FE	Y	Y	Y	Y	Y	Y

Treated bond defined by:	High emission industries			Below-median firm environmental score		
Ownership (%) by	All institutions	Mutual funds	Insurance firms	All institutions	Mutual funds	Insurance firms
	(1)	(2)	(3)	(4)	(5)	(6)
Treated bonds * Post Paris Agreement	-1.237***	-0.0333	-1.209***	-0.426	0.265***	-0.675**
	(0.182)	(0.0594)	(0.239)	(0.241)	(0.0635)	(0.234)
Treated bonds	0.297	0.780	-0.516	4.759***	2.921**	1.802
	(1.081)	(0.826)	(1.374)	(1.335)	(1.001)	(1.668)
Ln(Issue amount)	-7.633***	1.148	-8.812***	-3.633**	2.965**	-6.747***
	(1.007)	(0.687)	(1.241)	(1.210)	(0.983)	(1.475)
Years to maturity	-0.00141	-0.214***	0.222**	-0.107	-0.258***	0.160
	(0.0705)	(0.0288)	(0.0781)	(0.0882)	(0.0502)	(0.103)
Credit rating (numerical)	-0.554***	-1.110***	0.563**	0.195	-1.458***	1.667***
	(0.153)	(0.183)	(0.190)	(0.182)	(0.270)	(0.328)
Observations	11082	11082	11082	7640	7640	7640
Adjusted R^2	0.112	0.191	0.094	0.075	0.219	0.140
Time FE	Y	Y	Y	Y	Y	Y

Appendix

Table A.1: Summary statistics – matched sample for yield spreads around the Paris Agreement.

This table shows summary statistics as of December 2014 (one year before the Paris Agreement)for the sample matched on the alternative environment variables. The environment variables are defined alternatively as one of the following: the firm has a below median environmental score (Panel A), the firm is in a top 15 carbon emissions industry (Panel B), the firm is in the top quartile of carbon emissions in 2014 (Panel C) and the firm is in the top quartile of carbon intensity in 2014, measured as tons of emissions divided by firm revenue in thousands of dollars (Panel D). The matched sample is formed by using one-to-one nearest neighbor Mahalanobis matching of treated bond issues to control bond issues by oil beta, issue principal outstanding, time to maturity and credit rating as of year-end 2014. Spread, and profitability, are winsorized at the 1% and 99% levels. The ratings variable is assigned such that a higher number indicates a better rating. *, ** and *** indicate 10%, ** 5% and *** 1% significance respectively.

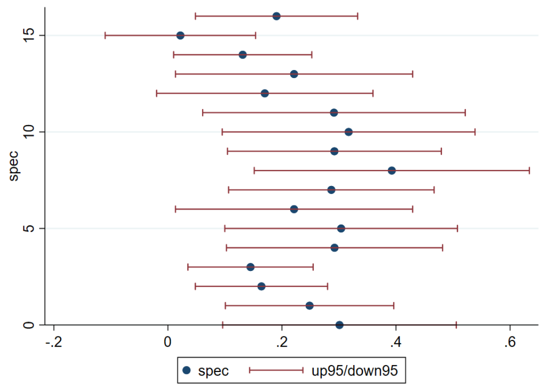
Group	**Sample**			**Control**			Diff Mean
Variable	Obs	Mean	St. Dev.	Obs	Mean	St. Dev.	
Panel A: Below Median Environmental Score							
Security-Level Variables							
Credit Rating	448	13.493	2.47	448	13.714	2.331	-0.221
Spread	448	2.011	1.283	448	2.004	1.388	0.007
Time to Maturity	448	9.46	7.447	448	9.541	7.406	-0.081
Firm Level Variables							
Profitability	129	0.233	0.196	110	0.25	0.191	-0.017
Oil Beta	129	0.011	0.032	110	0.001	0.032	0.01**
Panel B: High Carbon Emissions Industry							
Security Level Variables							
Credit Rating	646	15.265	2.761	646	15.317	2.804	-0.052
Spread	646	1.565	1.244	646	1.38	0.927	0.185***
Time to Maturity	646	11.131	8.902	646	11.219	8.924	-0.088
Firm Level Variables							
Profitability	135	0.187	0.139	114	0.288	0.22	-0.101***
Oil Beta	135	0.006	0.033	114	0.003	0.031	0.003
Panel C: Top Quartile Carbon Emissions							
Security Level Variables							
Credit Rating	252	15.905	2.47	252	15.813	2.33	0.092
Spread	252	1.292	0.787	252	1.268	0.917	0.024
Time to Maturity	252	11.937	9.504	252	12.049	9.521	-0.112
Firm Level Variables							
Profitability	39	0.161	0.121	64	0.225	0.188	-0.064*
Oil Beta	39	0.004	0.032	64	-0.001	0.029	0.005
Panel D: Top Quartile Carbon Intensity							
Security Level Variables							
Credit Rating	217	15.212	2.165	217	15.263	2.182	-0.051
Spread	217	1.413	0.83	217	1.311	0.907	0.102
Time to Maturity	217	11.791	9.412	217	11.818	9.493	-0.027
Firm Level Variables							
Profitability	38	0.134	0.09	64	0.228	0.165	-0.094***
Oil Beta	38	0.002	0.029	64	-0.004	0.025	0.006

Table A.2: Specifications in Sensitivity Analysis

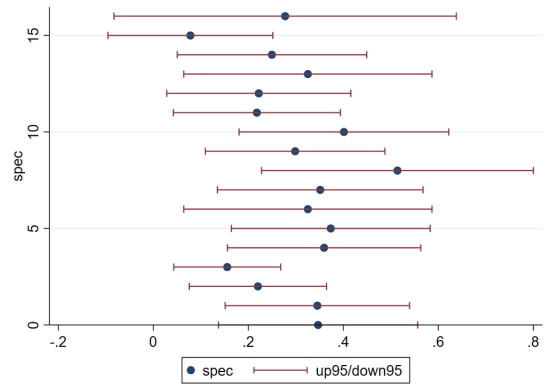
Specification #	**Caliper**	**Controls**
0 (i.e. main results)	1	Oil Beta, Ln(Principal Outstanding), Rating and Time to Maturity
1	0.75	Oil Beta, Ln(Principal Outstanding), Rating and Time to Maturity
2	0.5	Oil Beta, Ln(Principal Outstanding), Rating and Time to Maturity
3	0.25	Oil Beta, Ln(Principal Outstanding), Rating and Time to Maturity
4	1.25	Oil Beta, Ln(Principal Outstanding), Rating and Time to Maturity
5	1.5	Oil Beta, Ln(Principal Outstanding), Rating and Time to Maturity
6	1	Oil Beta, Ln(Total Assets), Rating and Time to Maturity
7	1	Oil Beta, Ln(MV Equity), Rating and Time to Maturity
8	1	Ln(Principal Outstanding), Rating and Time to Maturity
9	1	Oil Beta, Profitability, Ln(Principal Outstanding), Rating and Time to Maturity
10	1	Oil Beta, Ln(Principal Outstanding), and Rating
11	1	Oil Beta, Time to Maturity, and Rating
12	1	Oil Beta, Ln(Principal Outstanding, and Time to Maturity
13	1	Oil Beta, Ln(Principal Outstanding), Ln(Total Assets, Rating and Time to Maturity
14	1	Oil Beta, Ln(Principal Outstanding), Annual Stock Return, Rating and Time to Maturity
15	1	Oil Beta, Ln(Principal Outstanding), Annual Stock Return, Ln(Asset Size), Rating and Time to Maturity
16	1	Oil Beta, Ln(Principal Outstanding), Rating and Time to Maturity. Matched within industry.

Fig. A.1. Sensitivity Analysis of Yield Spread Difference-in-differences analysis.
This figure displays displays results for different specifications of the difference-in-differences analysis. Specifications detailed in Table A.2. Note that Specification 16 excluded for the high-emission industry because matching is conducted within industry for that specification.

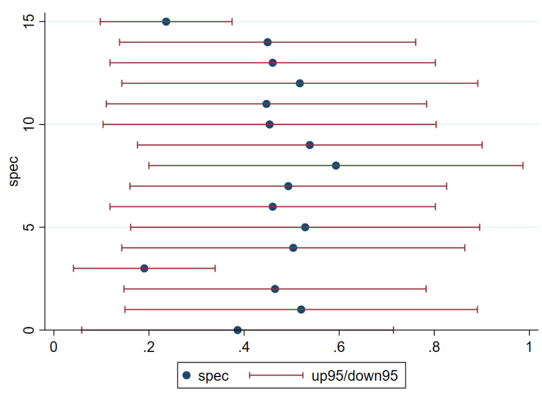
(a) $EnvProf_j = TopQtEmissions_j$



(b) $EnvProf_j = TopQtCarbonInt._j$



(c) $EnvProf_j = HighEmissionsInd_j$



(d) $EnvProf_j = BelowMedEnv_j$