Climate Regulatory Risks and Corporate Bonds

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Abstract

We examine how climate and other environmental regulatory risks affect bond risk and pricing. We find that bond credit ratings and yield spreads appear to be jointly determined by a firm's environmental performance and its regulatory conditions. Polluting firms and firms with poor environmental performance tend to have lower credit ratings and higher yield spreads, particularly when the firm is located in states with more stringent environmental regulation. Using the Paris Agreement as a shock to expected climate regulation, we provide evidence of a causal relation between climate regulatory risks and bond credit ratings and yield spreads.

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Recently investors have become more concerned about the environmental, social and governance (ESG) risks that bonds face, particularly climate risks.[1] In fact, research shows that climate risk is an important factor in institutional investor decisions and it affects firm leverage, the tail risk of stocks and the pricing of stocks and municipal bonds in the cross-section (Krüger et al., 2019; Ginglinger and Moreau, 2019; Ilhan et al., 2019; Bolton and Kacperczyk, 2019; Painter, 2019). Of the three components of climate risk (physical, transitional and regulatory), regulatory risk is the one that investors believe has already started to materialize (Krüger et al., 2019), which suggests that regulation is a major channel through which bond issuers internalize the costs associated with climate risk and other types of environmental risks. This is the question we address in this paper — whether firms' exposures to climate and other environmental regulatory risks affect their bond credit ratings and yield spreads.

In order to understand how bond market participants perceive firms' exposures to climate as well as other environmental regulatory risks, we consider how a firm's environmental performance interacts with its regulatory setting. That is, regulatory costs for environmentally-detrimental behavior become important because they force firms to bear costs for externalities that they otherwise might not be held responsible for covering. These environmental regulatory costs can have significant effects on firms' operating costs and cash flows.[2] More importantly, regulatory uncertainty itself poses costs to firms and their investors (Pindyck, 1993). Consequently, we hypothesize that bond market parameters become more affected by a firm's environmental profile when regulatory risks are more prominent.

Given this hypothesis, we focus on a firm's climate and environmental regulatory risk exposure through measures of the firm's environmental profile as well as measures of the firm's regulatory risk exposures. We capture environmental profiles through alternative measures: an industry categorization, that is, whether the firm belongs to a Top 15 Polluting Industry as defined by Ilhan et al. (2019) and a third-party ESG rating agency's assessment of the firm's environmental quality (Sustainalytics).

A firm's regulatory risk exposure derives from the firm's regulatory setting, which depends on the firm's location. In the United States, individual states are generally responsible for enforcing

[1] See, for example, Shultz (2017) and Furtado (2017).
[2] See for example, Karpoff et al. (2005).

federal and state environmental policies. Despite the fact that environmental laws are relatively uniform at the federal level, a wide variation exists across states in their approach to environmental regulatory rules and the stringency in implementation of those rules (such as through inspection and enforcement). This creates variations in the regulatory risks firms face, even when they have objectively similar levels of environmental quality.

To test our hypotheses regarding climate and environmental risk, we examine how bond credit ratings and yield spreads are related to firms' environmental profiles, taking into consideration the regulatory structure of the states in which they are located. That is, we test whether a newly issued bond's credit rating (or its offering yield spread) is related to the issuer's environmental profile (proxied through membership in a top polluting industry or the firm's Sustainalytics environment score), its home state's regulatory enforcement intensity, and the interaction between the two. We find the effects to be both statistically and economically significant. For example, a one standard deviation increase in the strictness of states' regulatory regimes is correlated with about a 1.7 notch decrease in credit ratings for firms in polluting industries relative to firms outside those industries. Similarly in the bond pricing tests, for firms that are located in states with stricter environmental enforcement policies, those that have lower quality environmental profiles have larger yield spreads on their bonds relative to firms with higher quality environmental profiles.

Because the relationship between a firm's environmental policies and its risk may be endogenous, we consider a mechanism to test for a causal relationship between firms' climate and environmental risk exposures and their bonds' ratings and spreads. One such mechanism derives from the observation that climate change regulatory risk appears to have increasing importance for investors. As Krüger, Sautner, and Starks (2019) have shown in their survey on climate risk, 55% of the institutional investors believe that the regulatory risk of climate change is already materializing and another 36% believe that it will materialize within the next few years. Consequently, we employ the December 2015 Paris Agreement as a shock to the regulatory environment. The Agreement has been signed by 196 governments who have agreed to take actions to limit global temperature increases.[3] When the Agreement was announced, a natural implication that investors could draw

[3]The fact that so many nations would sign on to the Paris Agreement was not foreseen far in advance of the UN Climate Change meeting in December 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 were still divisions among the world's leading countries regarding a deal. As late as Nov 23, the EU's climate and energy czar warned that an agreement was far from certain.In addition, as we show in a Google Trends analysis, there was little search for the

was that governments (including US state governments) would increase their enforcement of environmental rules related to mitigation of climate change, which suggests that US firms located in the states with more stringent enforcements of the rules would face greater regulatory risk.[4]

To test the hypothesis that the Paris Agreement would have affected firms with more climate regulatory risk exposure relative to other firms, we employ difference-in-differences analyses and make two comparisons for the changes in credit ratings and yield spreads: between top polluting firms and other firms and between firms with low environmental scores and firms with high environmental scores. Our sample for these tests consists of bonds issued before July 2015 and traded during the testing period. Controlling for time invariant firm characteristics and macroeconomic trends, we find that after the Paris Agreement, bonds from firms in top polluting industries experience an average 0.59 notch credit rating decrease relative to other firms. These results support the hypothesis that bond credit ratings for top polluting firms are affected by changes in climate regulatory risk. Similarly, we find that firms with environmental scores below the median experience an average decrease in rating of 0.53 notches relative to firms with scores above the median. This evidence suggests that credit rating agency analysts are concerned about expectations of regulatory changes when evaluating the impact of climate risk on a firm's default risk.

Evidence also suggests that investors appear to be concerned about expectations of regulatory changes. We find similar types of effects for bond spreads after the passage of the Paris Agreement, whether we employ the polluting firm classification, in which relative spreads for bonds issued by polluting firms increased by about 43 bp, or we employ the Sustainalytics environmental classification, in which case the relative spreads for firms with scores below the median increased by about 50 bp after the Paris Agreement relative to the other firms.

If our results are due to climate risk affecting bond issuers through the channel of climate regulation, we would further expect that the results should be stronger in the states with the strictest regulations. Consequently, to further test our hypothesis, we conduct a triple difference analysis in which we include an indicator variable for firms headquartered in states with the strictest regulatory programs as reflected in their relative number of enforcements. The analysis shows that

topic "Paris climate talks" or "United Nations climate change conference" before late November 2015.

[4]For example, Brian Cahill, a Moody's Managing Director, stated that the voluntary nature of a country's actions "makes more detailed assessment of the credit impact of the Paris Agreement difficult, although the trend is clear and broadly negative for those sectors with the highest exposure to carbon emissions regulation that we have identified." (Moody's, 2015)

following the Paris Agreement, the decrease in ratings for top polluting firms relative to other firms tends to be concentrated in the states where regulatory enforcement is stricter. We find that for polluting firms in these states, the average credit ratings decrease approximately 0.6 notches and the average yield spreads increase approximately 60 bps relative to those located in the lower regulation states.

Given the significant uncertainty associated with enforcement of climate regulations, we additionally hypothesize that although polluting firms' ratings decrease and bond spreads increase, on average, not all participants in the corporate bond market agree on the degree to which climate regulatory risk should affect a given firm's default risk. The heterogeneity in investor responses could be expected because news about climate regulation tends to be soft information that cannot be easily summarized in the form of discrete quantitative measures such as credit ratings, which could thus increase the potential for disagreement across market participants (Liberti and Petersen, 2018). In particular, given their different goals, credit rating agencies may evaluate climate regulatory risks differently from each other.[5] To test this hypothesis, we examine the effects of the Paris Agreement on credit rating deviations for top polluting firms relative to other firms. We find that after the Paris Agreement, the rating differences between Moody's and S&P increase, on average. The results suggest that while the Paris Agreement had an impact on credit ratings, market participants still face considerable uncertainty in forecasting the impact of climate regulation on future cash flows.

Our results are important on a number of dimensions. First, given the evidence on institutional holdings of firm equity in the face of poor environmental performance (Fernando et al., 2017), it is an empirical question whether and how bond prices would react to poor environmental performance. Our results establish that bond investors demand higher interest rates from issuers with poor environment performances, which is consistent with earlier work on bank loans (Chava, 2014). The results are also consistent with the evidence on climate risk and municipal bonds (Painter, 2019) as well as the evidence regarding carbon premia in equity markets (Bolton and Kacperczyk, 2019).

Our paper also contributes to the literature on the relation between ESG, in general, and bond prices. For example, there exists work showing a strong relation between country ESG

[5] As pointed out by Bongaerts et al. (2012), credit rating agencies do not have the same goals. S&P and Fitch aim to reflect cross-sectional variation in default probabilities while Moody's has the additional gol of incorporating the bond's expected loss given a default and the dispersion of these expected losses across firms.

characteristics and the pricing of their sovereign bonds (Margaretic and Pouget, 2018; Capelle-Blancard et al., 2019). We contribute by showing that ratings and spreads for corporate bonds are affected by not only a firm's environmental activities but also their regulatory risk exposure. Similarly, our paper is related to Amiraslani et al. (2017) and Jiraporn et al. (2014) in that we also examine the relationship between some aspect of ESG and measures of bond risk and pricing. However, these papers examine the relation between a firm's social capital (as reflected by the firm's CSR rating) and the firm's bond spreads or a firm's ESG scores and the firm's credit rating, while our focus is on the relation between a firm's environmental actions and quality and perceptions of the firm's riskiness as reflected in its credit ratings and yield spreads. We also differ from Amiraslani et al. (2017) in that we are specifically interested in regulatory risk as a channel through which environmental risks matter for bond pricing, while their shock is the 2008 financial crisis, which they argue makes trust more important to investors.

Our paper is related to several papers that use political changes regarding environmental issues to examine how prospects for future governmental actions can affect different aspects of firms' actions and investor expectations. Ramelli et al. (2018) examine the stock market reactions to Donald Trump's election and the appointment of Scott Pruitt to lead the EPA, two events that seem to reflect the changing political assessment of environmental issues in the US. Ginglinger and Moreau (2019) examine the relation between climate risk and firms' capital structures. They provide evidence that firms reduced their leverage after the Paris Agreement and that this reduced leverage effect derived from both a demand effect on the part of the firm and a supply effect on the part of lenders, especially bankers. Our paper is complementary in that we find decreased credit ratings and higher yield spreads suggesting that the Paris Agreement increased costs of debt for firms in top polluting industries with more stringent regulatory oversight.

Our paper is also complementary to that of Ilhan et al. (2019), 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 analyses and results are consistent in finding credit ratings to be decreasing after the Paris Agreement for the highest polluting industry firms located in stricter regulatory environments, which suggests increasing perceived climate regulatory risk. We also focus on risk and acknowledge that the most important risk for the bondholders would

be the downside risk examined in Ilhan et al. (2019), but our interest is in the rating agency and bondholder perceptions and actions, while their interest is in the equity holders' perceptions and actions. The results between the two papers are supportive of the hypothesis that climate regulatory risk is an important factor in the pricing of securities.

We also contribute to the literature on the effects from environmental regulatory risks. Previous work has examined the stock market response to negative environmental regulatory news. For example, Karpoff et al. (2005) find that a firm's equity investors respond negatively to new information regarding EPA violations and that this response is tied to the expected legal penalties. Our focus is on how bond investors respond to changes in perceptions of firms' environmental regulatory risks.

I. Data

A. Sample Construction

Our sample includes bonds issued by US 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.[6] 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 and Sustainalytics. We use Mergent FISD for characteristics of the bonds such as offering terms, bond maturity, the principal amount outstanding and bond ratings. We use Moody's ratings as the primary source of credit ratings. If Moody's did not rate the security, the S&P rating is used instead. If neither Moody's nor S&P rate the bond, the Fitch rating is used. We transform the bond rating to a quantitative measure by assigning each rating a numerical value, with the lowest rating (D) receiving a value of 1 and increasing by 1 for each notch such that the Aaa rating (or the S&P and Fitch equivalent) receives a value of 22.

We combine the Mergent FISD bond characteristics data with data on secondary market pricing for corporate bonds from the TRACE database.[7] We calculate monthly bond yields as the median

[6]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 placement and Rule 144A bonds, variable rate bonds and zero coupon bonds

[7]Data errors in TRACE are filtered following the procedure in Dick-Nielsen (2009).

yield on all trades of that security occurring on its last active-trading day of a given month.[8,9] Yields are linearly interpolated for months with missing yields. Observations with either missing ratings or which do not have enough information to linearly interpolate a yield are dropped. The risk-free rates are obtained from the US Treasury to calculate yield spreads.[10]

We further obtain data for the issuing firms through CRSP and Compustat, using the six-digit CUSIP, year and month to merge the databases.[11] We define polluting industries using the two-digit SIC classification as in (Ilhan et al., 2019).[12] In addition to the polluting industry indicator, we also measure a firm's environmental profile using ratings provided by Sustainalytics. Sustainalytics reports proprietary ratings along many dimensions within the environmental, social, and governance spheres from August 2009 through August 2017. The Sustainalytics Environment Scores are calculated based on 57 environmental indicators and range from 0-100, with a higher score indicating stronger environmental performance. The main variable we employ is the summary Environment Score, which is calculated as a weighted average of the indicators, where the weights used are industry specific and proprietary, so environment scores are industry adjusted. Sustainalytics uses a variety of sources including firm code-of-conducts, UN documents, SEC filings, CSR reports, news reports and materials from NGOs and other non-profit organizations. We merge the corporate bond data with the Sustainalytics data by ticker, year, and month.

B. State Environmental Regulation Data

US environmental policy is designed as a shared responsibility between the federal government and the individual states — the EPA sets the federal environmental policy and individual states are typically the parties that are supposed to enforce the policy. In particular, state personnel conduct

[8] All trades deviating from the daily median price for that security by greater than 10% are dropped. Additionally, all price reversals greater than 10% are dropped. These additional steps are suggested by Edwards et al. (2007).

[9] Trades for equity-linked-notes reported in TRACE are excluded, as well as those with missing CUSIPs.

[10] The Treasury provides data on one month, three month, six month, one year, two year, three year, five year, seven year, 10 year, 20 year and 30 year bonds. For other maturities, we linearly interpolate rates using available data. Month-end Treasury rates are used in calculating yield spreads.

[11] In the merger we drop all observations with missing ticker, missing fiscal year, missing total assets, or missing market value. Data on firm characteristics comes from Compustat. From CRSP, it is possible to obtain a unique mapping of 6 digit CUSIP and ticker by time period, which we use to merge with TRACE.

[12] In particular, Ilhan et al. (2019) rank two digit SIC industries by average carbon emissions between 2010 and 2017. The authors display the Top 15 Polluting Industries in Table 2 of their paper. By this classification, polluting industries are Petroleum & Coal Products, Primary Metal Industries, Electric, Gas & Sanitary Services, Transportation by Air, Trucking & Warehousing, Water Transportation, Oil & Gas Extraction, Railroad Transportation, Stone, Clay & Glass Products, Paper & Allied Products, Metal Mining, Non-Classifiable Establishments, Chemical and Allied Products, General Merchandise Stores and Textile Mill Products.

inspections to evaluate compliance with regulations and they issue enforcement actions if they come to the conclusion that compliance standards are not being met. Federal enforcement protocol is such that states are authorized and expected to enforce EPA regulations for violations within the state using as a minimum the regulatory standards established by the EPA. States are allowed to create and enforce laws stricter than EPA regulations, are expected to handle enforcement at least as stringently as EPA standards. Since some states enforce regulations with the bare minimum standards and others enforce them more strictly, this allows us to observe cross-sectional variation in regulatory standards.

We use EPA enforcement data provided in the Integrated Compliance Information System for Federal Civil Enforcement Case Data to measure exposure to environmental regulatory actions. We construct two measures of exposure to regulatory costs by following a methodology from the political science literature (Konisky, 2007). These measures capture enforcement actions for the Clean Water Act (CWA), Clean Air Act (CAA) and Resource Conservation and Recovery Act (RCRA), which arise due to violations occurring in facilities located in a given state in a given year. We construct two measures for total enforcement activity in a state. The first is the number of enforcement actions, which include both informal enforcement actions, such as notifications of violation, and formal actions such as fines and administrative orders to force the violator to take action to comply with the regulation. The second measure we construct is the number of inspections conducted within a given state. Both the number of inspections and the number of enforcement actions are normalized by the total number of facilities regulated by the EPA in the state. 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 states where the EPA is responsible for enforcement. [13] This state-year measure is then merged with our data by the firm's headquarters state and year. Our final dataset contains 3,928 corporate bonds, corresponding to 451 firms.

C. Summary Statistics

In Table I we report the sample summary statistics. The data covers the 2009-2017 period. The average Environment Score in the sample is about 54.9, a little higher than the halfway point

[13] 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 here `https://www.epa.gov/compliance/state-review-framework-compliance-and-enforcement-performance`.

of the 0-100 range. The standard deviation of the scores is 13.2. About 41.1% of all firms in the sample belong to a polluting industry. While this is a large percentage of the sample firms, it is reasonable considering many of the polluting industries are economically important and contain a large number of bond issuers.[14]

The average bond in the sample has a maturity of 10 years, which is on the longer end of mid-term maturity. The average credit rating variable in the sample is about 14.7, which is in between a Bbb2 and Bbb1 rating. The average bond in our sample has a yield spread of 1.662% with a standard deviation of 1.605%, indicating a substantial variation in spread. On average, each state engages in 0.6 regulatory enforcements and 0.7 inspections per total number of facilities present in the state each year. However, the table shows that large variation exists in enforcements and inspections, with each having a standard deviation of about .9. This indicates that there are certain instances where states issue a large number of enforcement actions in a given year. There are slightly more inspections than enforcement actions, which is expected as inspections need not end in enforcement actions, but all enforcement actions must begin with an inspection.

II. Relationship between regulatory strictness and bond risk

A. Regression Design

We first design tests to examine whether a firm's environmental profile (measured through the polluting industry categorization or the Sustainalytics score) affects the firm's exposure to environmental regulatory risk as reflected in the firms' bond credit ratings and offering yield spreads. In separate regressions we use the bond ratings and the offering yield spreads of a firm's newly-issued bonds as the dependent variables. The key independent variables are the firm's environmental profile, the regulatory enforcement intensity of the firm's headquarters state, and the interaction between the two variables:

[14] In comparing our sample of firms to the full sample of firms in Compustat, we find a similar percentage of firms that are described as being in a polluting industry using this definition.

$$Rating_{it} = \beta_1 EnvProf_{jt-1} + \beta_2 Reg_{st-1} + \beta_3 (EnvProf_{jt-1} * Reg_{st-1}) + \beta_4 X_{it-1} + \gamma_t + \kappa_s + \epsilon_{it}, \tag{1}$$

$$Spread_{it} = \beta_1 EnvProf_{jt-1} + \beta_2 Reg_{st-1} + \beta_3 (EnvProf_{jt-1} * Reg_{st-1}) + \beta_4 X_{it-1} + \gamma_t + \kappa_s + \epsilon_{it}. \tag{2}$$

We focus on at-issue bonds in order to better capture the relation between environmental regulatory risk exposure and firms' cost of debt because credit ratings and offering spreads at the bond's original issue better capture the costs firms face when issuing debt. Additionally, at-issue bond spreads are less noisy than trading yields. We proxy for a firm's environment profile through the Sustainalytics Environment Score as well as an indicator for whether the firm is a member of a top polluting industry according to Ilhan et al. (2019).[15] Regulatory exposure is proxied for using state-level EPA inspections or punishments.

In regression equations (1) and (2), the main parameters of interest are β_3, which capture the interactions between the firms' environmental profiles and the regulatory conditions the firms face. Based on our hypothesis, we expect the coefficient β_3 to be negative when rating is the dependent variable and regulatory risk is interacted with the polluting industry indicator. Similarly, we expect the coefficient β_3 to be positive when rating is the dependent variable and regulatory risk is interacted with the firm's Environment Score. We expect the opposite signs in the corresponding regressions where spread is the dependent variable, since risky debt generally has high spreads with low ratings. All regressions include month fixed effects γ_t and state fixed effects κ_s, so the results control for macroeconomic trends and time invariant state characteristics.

B. Results

Results for the regression in Equation 1 are shown in Table II. Column (1) reports the results for top polluting firms. Just being a member of a top polluting industry by itself does not affect a firm's bond credit rating nor does residing in a state with more EPA inspections. However, being a top polluting firm in a state with more inspections does appear to affect the bond's credit rating. That

[15] See footnote 12 for the list of industries.

is, examining the interaction effect between being a top polluting firm and the state-level regulatory risk, proxying for regulatory risk using the number of inspections conducted each year, the results in Column (1) show a significantly negative effect. We find that a one standard deviation increase in a state's number of inspections is correlated with about a 1.7 notch decrease in ratings for firms in polluting industries relative to those outside of polluting industries. In Column (2) we find similar results for firms based on their Sustainalytics environment scores. In this case, a one standard deviation increase in the firm's environment score is correlated with a 1.1 notch improvement in ratings for those firms observed in a state-year with an average number of inspections. While this effect is already substantial, a one standard deviation increase in the number of inspections heightens this effect by an additional 1.1 rating notches. This finding suggests that credit rating agencies recognize the regulatory stringency of the firm's location when evaluating how the firm's environmental profile affects its bond ratings and yield spreads.

In Columns (3) and (4) we proxy for states' regulatory strictness using the number of enforcement actions. While the coefficient on the interaction term between Environment Score and state regulatory strictness in Column (3) is not statistically significant, the results in Column (4) imply that a one standard deviation increase in Environment Score is correlated with a .8 notch increase in ratings for firms located in a state-year with an average number of enforcements, and when combined with a one standard deviation increase in the number of enforcement actions this effect heightens by an additional .6 notches.

The results in Table II also imply that credit rating agencies consider regulatory risk when evaluating how environmental concerns impact bond investors. When examining the policies of credit rating agencies this implication is particularly pertinent. According to methodology published in 2018, Moody's states that they consider both the direct environmental implications and the regulatory costs when evaluating ESG's impact on credit ratings. However, they consider regulation more closely as it is easier to forecast the impact of regulation (Moody's, 2018). The credit rating agencies appear to recognize that regulation is the most direct channel through which firms face potential monetary costs for their environmental actions. Based on the Moody's methodology then, it seems reasonable that the effects of detrimental environmental activities on bond ratings should be sensitive to strictness of states' EPA regulation enforcement.

Table III displays the results of tests of the hypotheses that firm's environmental profile expo-

sures are also incorporated into their offering yield spreads in which we examine the relationship between a firm's environmental profile and its bonds' offering yield spreads.[16] It is particularly useful to examine bond offering spreads as they are determined prior to the initial offering of a new bond. Therefore, it provides a less volatile estimate of the market's view of an issuer's cost of debt in this bond issue.

The results on bond offering yields are more mixed than those of credit ratings shown in Table II. On the one hand, when we use polluting industry classification as a measure for environmental risks, it does not seem to affect bond pricing, even when firms are located in high-enforcement states. Column (1) shows that being a polluting firm, even in a state with stricter enforcement, does not imply a relationship with the yield spread on the firms' bonds. On the other hand, when we use the Sustainalytics Environment score as the measure of the firm's environmental profile, we find that environmentally friendly firms appear to be able to issue bonds at lower yield spreads and this effect is even stronger in states with strong EPA enforcement. Column (2) shows that a one standard deviation increase in a firm's Environment Score is correlated with a 46.2 bp decrease in spread, which is consistent with Chava (2014) who finds that firms with higher environmental scores have lower interest rates on their bank loans implying that they face lower risks. When we consider the effects of the regulatory environment, we find that the effects are enhanced. An additional one standard deviation increase in the number of inspections is predictive of an incremental 69.4 bp decrease in spreads. Column (4) shows that a one standard deviation increase in the Environment Score is predictive of a 25.2 bp decrease in spreads, and when combined with a one standard deviation increase in the number of state regulatory penalties it predicts an additional 27.2 bp decrease in spreads. These results suggest that bond investors also consider regulatory risk when estimating issuer cost of debt through the bond issue. That is, investors seem to believe that bad environmental policies have a more negative impact on issuer cost of debt if the issuers are located in a regulatory climate in which there exists a greater expectation of regulatory actions for their activities.

Our results in Tables II and III show that environmentally-friendly firms tend to have better credit ratings and lower spreads, especially in states where environmental regulation is more stringent. Presumably, this is because firms in states with stricter regulation are more likely to face

[16] In these regressions we do not control for bond rating.

regulatory costs such as fines or possibly reputation losses, even if they have poor environmental practices, which in turn increases their default risks.[17] If firms are located in states where regulation is not enforced as strictly, the channel through which poor environmental practices would lead to increasing default risk is not clear. This result is consistent with a literature that shows that pollution has greater negative consequences under stricter regulatory regimes, implying strictness in regulation forces firms to internalize the costs of pollution (Greenstone, 2002). To better understand this effect, we consider a specific change in expectations of the passage of new regulations to examine whether this change led to worsening ratings and spreads for less environmentally friendly firms. In particular, to exploit exogenous shocks to environmental regulatory risks that firms face, we use difference-in-differences analyses surrounding the Paris Agreement as an identification strategy.

III. Difference-in-Differences: The Paris Agreement

A. Shock: The Paris Agreement

Endogeneity may bias the estimates of β_3 in Equations 1 and 2. For example, states may have strict regulations because they have other types of favorable conditions attracting polluting industries. To mitigate this type of endogeneity problem, we exploit a shock that increases the climate regulatory risks faced by firms, while not changing either the performance of firms or impacting how environmentally friendly the firms are. Such a shock increases costs for firms with environmental deficiencies relative to those that do not have such definciencies. For example, after the shock one would expect the bonds of firms with poorer environmental profiles to be perceived as more risky relative to the bonds of firms with better environmental profiles.

The shock to regulatory risks that we employ is the Paris Agreement on December 12, 2015. The main aim of the Paris Agreement is to limit global temperature rise in this century to 1.5 degrees Celsius above pre-industrial levels. As such the Agreement calls for mitigation measures to reduce emissions with sufficient speed to achieve this goal. Countries signing onto the Agreement are responsible for submitting national action plans that at a minimum are as ambitious as those described in the Agreement. Of course, these plans would be expected to include a regulatory

[17] Although Karpoff et al. (2005) conclude there are no reputational losses for EPA violations in 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.

response to induce firms to behave consistently with the goals of the Paris Agreement. The Agreement served to create the expectation that more stringent environmental regulations would soon be put into place. Thus, we expect this Agreement to negatively affect firms with high pollution relative to firms that do not have such pollution.

To test this expectation, we conduct difference-in-differences regressions to compare the credit ratings and yield spreads of top polluting versus other firms before and after the Paris Agreement. Our tests also compare firms with different environmental scores before and after the Agreement by sorting firms by their Sustainalytics Environment Score as of July 2015, or five months before the Agreement. Firms with Environment Scores above the sample median are designated as "High Environment Score Firms" and those with Environment Scores below the sample median as "Low Environment Score Firms." We employ the scores as of July 2015 to counteract possible anticipation of the outcome of the Paris climate talks. As pointed out earlier, a large amount of uncertainty existed regarding whether the countries would actually come to an agreement even just days before the Agreement was announced. Figure 1 displays Google Trend data on searches related to the Paris climate talks between January 1, 2015 and December 31, 2016. There were very few searches related to the Paris climate talks prior to the end of November 2015, and searches spiked in December 2015.[18] This Google Trends data can be generalized to provide evidence there was not widespread interest in the Paris climate talks prior to the Agreement, and given the questions about whether the nations would actually come to a consensus suggests that the Agreement was not well-anticipated by bond market participants.

A.1. Credit rating tests

We examine the bond credit ratings in the two-year period from 12 months before to 12 months after the Paris Agreement through the following regressions:

$$Rating_{it} = \beta_1(PollutingIndustry_j * AfterParis_t) + \gamma_i + \kappa_t + \epsilon_{it}, \tag{3}$$

$$Rating_{it} = \beta_1(BelowMedEnv_j * AfterParis_t) + \gamma_i + \kappa_t + \epsilon_{it}, \tag{4}$$

[18] We also examined the related topics of "United Nations Climate Change Talks" and "Paris Agreement." For both of these other Google Search Trends topics, there was little search prior to the end of November 2015.

where $AfterParis$ is a dummy for periods in December 2015 or the following 12 months.

In the sample, β_1 is equal to the change in ratings for either polluting firms relative to other firms or firms with Below Median Environment Scores relative to those with Above Median Environment Scores following the Paris Agreement. γ_i and κ_t are security and time fixed effects. The effect captured is the impact of having a poor environmental profile following the Paris Agreement, controlling for time invariant firm characteristics and for macroeconomic trends affecting all firms equally. In constructing our sample, we include a pre-period of one year prior to the Agreement and a post-period of one year following the Agreement, so our sample runs from December 2014 through November 2016. The panel is constructed as a balanced panel, limiting our sample to securities for which it is possible to observe data in all months of our sample period in all tests.

To begin, we graphically examine ratings for firms in the control and the treatment group in each test. We run the following regression:

$$Outcome_{it} = \sum_{k=-11}^{11} \beta_k[(t = k) * EnvTreat_j] + \gamma_i + \kappa_t + \epsilon_{it}. \quad (5)$$

We begin with $Outcome_{it}$ as the bond credit rating. This gives a treatment effect for each period in our sample, which allows us to easily examine whether the parallel trend assumption is violated. The interacted time dummy for the first period (November 2014) is excluded, so all treatment effects are relative to November 2014. Results for this regression examining the effect of belonging to a top polluting industry are shown in Figure 2(a). The blue line and dots indicate the coefficient estimates, and the red and green lines are bands of a 95% confidence interval. The treatment effect is not statistically significantly different from zero in the entire pre-period. The treatment effect becomes statistically significant and negative in February 2016. A similar graph examining the effect of having a Below Median Environment Score is shown in Figure 2(b). The results are very similar, although somewhat weaker just as is apparent in the group averages. However, they are still large and statistically significant. These charts provide reasonable evidence that the parallel trends assumption is likely satisfied.

Table IV displays the results of the difference-in-differences regression. Columns (1) and (3) display results with only a time fixed effect, which are statistically significant. Additionally, after adding the security fixed effect in Columns (2) and (4), the effects are just as large and statistically

significant. In Columns (1) and (2), it is clear that controlling for time invariant firm characteristics and macroeconomic trends, top polluting industries on average experience a 0.59 notch ratings decrease following the Paris Agreement relative to other firms. Similarly, Below Median Environment Score firms experience an average decrease in rating of 0.53 notches following the Paris Agreement relative to above median Environment Score firms. This implies a direct consequence for firms that heavily pollute following the Paris Agreement. In particular, the results imply that following the Paris Agreement, slightly more than half of firms in top polluting industries receive relative downgrades while firms outside of those industries do not experience significant changes in their credit ratings, on average. These results provide evidence that credit rating agency analysts appear concerned about expectations of regulatory change when evaluating the effects of environmental risk on a bond's default risk.

A.2. Yield spread tests

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

$$Spread_{it} = \beta_1(PollutingIndustry_j * AfterParis_t) + \gamma_i + \kappa_{tp} + \epsilon_{it}, \tag{6}$$

$$Spread_{it} = \beta_1(BelowMedEnv_j * AfterParis_t) + \gamma_i + \kappa_{tp} + \epsilon_{it}. \tag{7}$$

Since the Paris Agreement is a time series shock, rather than using at-issue bonds as we have done in the previous analyses, we employ bonds issued before the sample period in order to exploit time-series variation induced by the shock. Thus, we use bond trading yield spreads from the secondary-market in the spread analyses.

To better control for noise in spreads and compare bonds with similar credit worthiness, we conduct a one-to-one Mahalanobis matching with replacement (Mahalanobis, 1936). The intuition behind this approach is that for every treated firm, the control firm that is the shortest distance from it is identified. This distance is calculated as of July 2015 using rating, size, profitability and time to maturity as covariates. The Mahalanobis measure weights the distance in terms of

covariance.[19,20] In this regression, instead of a time fixed effect a time-matched pair fixed effect κ_{tp} is included. As a result, this test can be interpreted as comparing the change in spread for a treatment security to its matched control security after the Paris Agreement, controlling for the treatment security's average spread over time.

Separate matched samples for the top polluting firm indicator and the Below Median Environment Score indicator are generated. Summary statistics for both matched samples are shown in Table V. In each sample, we provide summary statistics for the control and treatment group subsamples. We include all observations occurring in November 2015 or earlier so as to evaluate whether the control and treatment groups were similar prior to the Agreement. Panel 1 of the table examines the sample matched on the top polluting industry indicator and Panel 2 contains the sample matched on the below median environmental score indicator. The last column of the panel provides a difference in means tests between the control and the treatment groups. In many cases, the control group is quite different from the treatment group even after matching. This does not necessarily invalidate our difference-in-differences research design. We examine the parallel trend assumption graphically and it generally holds. Additionally, it is reasonable that the firms are different regardless of the matching, as we matched as of July 2015 and the summary statistics are taken for all observations occurring in November 2015 or earlier.

Turning to the effects of the Paris Agreement on bond spreads, we first run Equation 5 using membership in a polluting industry as treatment in Figure 3(a). The pattern here shows a sizable initial increase in spreads for top polluting firms relative to other firms. However, the effect is transient, and much of the initial impact reverses afterward, although it remains statistically significant throughout the entirety of the post-period. A similar pattern is observed in Figure 3(b). One explanation for these reversal patterns may be that it is unclear how much the Paris Agreement shock impacted US firms as there was substantial uncertainty surrounding the nature of policy that would ultimately result from it. In particular, the Agreement did not go into effect until November 2016. However, this was the same month that Donald Trump, a climate change skeptic, was elected President of the United States. Throughout his campaign, Trump expressed interest in leaving the

[19]We use a caliper of 0.35, meaning if for a given treatment firm there does not exist a control firm whose Mahalanobis distance is 0.35 or less, we drop it from the sample.

[20] It has been shown that with two or more continuous variables the Mahalanobis distance is biased. To address this, we use the appropriate bias adjustment in conducting the matching (Abadie and Imbens, 2006).

Paris Agreement, and finally did so in June 2017 (Shear, 2017). Thus, although the Paris Agreement could have affected investors' expectations of increased regulation regarding climate change in the United States, this change in expectations may have been short-lived for the investors.

Table VI displays our difference-in-differences regression results using spread as the dependent variable. The results are both large and statistically significant. Columns (1) and (3) contain results with only a time fixed effect and Columns (2) and (4) add a security fixed effect. Furthermore, as before, the results are similar whether they include or exclude the security fixed effect. Relative to other firms, spreads for bonds issued by top polluting firms increased by about 43 bp after the passage of the Paris Agreement. Furthermore, relative to firms with Above Median Environment Score, spreads increased by about 50 bp for firms with Below Median Environment Scores after the Paris Agreement.

These are substantial increases in bond spreads for firms with poor environmental profiles, implying that bond investors evaluated the debt of these firms very differently following the passage of the Paris Agreement. In particular, the results are consistent with the hypothesis that when investors developed expectations that these firms would soon need to abide by new regulations, they began evaluating the firms' bonds as more risky, leading to increases in bond spreads and thus, increases in the firms' cost of debt relative to more environmentally friendly firms. This result is consistent with other research showing that environmental policies are related to firms' costs of debt (Chava, 2014), that the Paris Agreement increased perceptions of downside risk (Ilhan et al., 2019) and that the Paris Agreement changed firms' leverage (Ginglinger and Moreau, 2019).

The result is also consistent with previous literature that shows that firms' cost of debt increases in political uncertainty risk (Bradley et al., 2016). It has also been shown that firms that are exposed to increased liability risk tend to suffer from indirect costs of bankruptcy (Gormley and Matsa, 2011). It seems likely that this effect should also be present in the context of increased regulatory risk. Since investors realize that polluting firms are more likely to bear costs of additional regulation, this could increase both the possibility of bankruptcy as well as the indirect costs of bankruptcy. The increased cost of regulation in turn makes debt issued by heavily polluting firms more risky and increases their cost of debt. The results indicate that it is not just bond ratings that change as a result of passage of environmental regulations. Rather, new regulation can have a real impact on firm fundamentals and investor evaluation of issuer cost of debt.

A.3. Triple-difference tests

Although the Paris Agreement could increase the prospect of future environmental regulatory risks, its impact on firms located in different states would be expected to differ because of the variations across state governments in their enforcements of environmental regulations. We hypothesize that states with tougher environmental regulation would be more likely to increase their scrutiny on environmentally deficient firms after the Paris Agreement. To examine this hypothesis, we conduct a triple-difference regression in which we include an indicator variable for firms headquartered in states with stricter regulatory environments. To define the stricter regulatory environments, we sort states by the number of EPA penalties issued in 2015 (the year in which the Paris Agreement occurred in December). States with above median penalties are defined as high regulatory enforcement states, and those with below median penalties as low regulatory enforcement states.[21]

Using these definitions, we run the following analyses:[22]

$$Rating_{it} = \beta_1(AfterParis_t * PollutingIndustry_j) + \beta_2(AfterParis_t * HighReg_s) \tag{8}$$
$$+ \beta_3(PollutingIndustry_j * HighReg_s) + \beta_4(AfterParis_t * PollutingIndustry_j * HighReg_s) + \gamma_t + \kappa_i,$$

$$Spread_{it} = \beta_1(AfterParis_t * PollutingIndustry_j) + \beta_2(AfterParis_t * HighReg_s) \tag{9}$$
$$+ \beta_3(PollutingIndustry_j * HighReg_s) + \beta_4(AfterParis_t * PollutingIndustry_j * HighReg_s) + \gamma_t + \kappa_i,$$

where the parameter of interest is β_6, which captures the impact of the Paris Agreement for polluting firms that are located in a Strict Regulatory Enforcement State relative to a Loose Regulatory Enforcement State. If β_6 is negative in Equation 8 and positive in Equation 9, this would imply that polluting firms suffered more after the Paris Agreement in states where they could expect any potential new regulations to be enforced more strictly. This suggests that the Paris Agreement would affect bond credit ratings and spreads because it affected firms' exposure

[21] In unreported tests we also conduct this test using an above median inspections indicator and get similar, albeit weaker results.

[22] We run the regression for Equation 9 using the matched sample created in running the difference-in-differences regression from Equation 6. Time fixed effects are used instead of time-pair fixed effects to allow for sufficient variation in regulatory strictness.

to regulatory risk. In this case only the top polluting industry indicator is used as the treatment, as new regulations would be expected to be aimed more at firms based on pollution, rather than their environmental scores overal.

To evaluate the effect graphically we examine the coefficients for the following regression:

$$Outcome_{it} = \sum_{k=-11}^{11} \beta_{k,E}[(t=k) * PollutingIndustry_j] + \sum_{k=-11}^{11} \beta_{k,R}[(t=k) * HighReg_j] + \sum_{k=-11}^{11} \beta_{k,R,E}[(t=k) * PollutingIndustry_j * HighReg_j] + \gamma_i + \kappa_t + \epsilon_{it},$$

where the parameters of interest are $\beta_{k,R,E}$, which are the period-by-period interactions between the polluting industry indicator and the high regulation indicator. Coefficients from the regression using bond ratings are shown in Figure 4(a). There is a clear decline in the rating for top polluting firms relative to other firms located in high regulation states compared to those located in low regulation states after the Paris Agreement was announced. Figure 4(b) shows the coefficients in the above regression where the outcome variable used is bond spreads. There exists a substantial increase in bond spreads for top polluting firms relative to other firms located in high regulation states as compared to those located low regulation states following the Paris Agreement. This result provides evidence that the effects of the Paris Agreement on top polluting firms' bonds documented earlier are likely driven by firms located in states that enforce environmental regulations relatively strictly.

Our triple-difference regression results are presented in Table VII. Columns (1) and (2) display results where the dependent variable is credit rating. The main parameter of interest is the triple-difference estimator $PollutingIndustry_j * HighReg_s * AfterParis_t$. The coefficient is negative and statistically significant in both columns, meaning the decrease in ratings for top polluting firms relative to other firms is more severe in states with stricter regulatory enforcement. Our estimate of β_4 in Equation 8 shows that ratings for bonds issued by polluting firms located in high regulation states on average dropped by about .6 notches relative to those located in low regulation states following the Paris Agreement. The magnitude of β_4 is much larger than that of β_1 indicating that the Paris Agreement had a much larger impact on ratings for polluting issuers located in strict regulation enforcement states than those located in weak regulation enforcement states.

Columns (3) and (4) display results regarding the impact of belonging to a polluting industry on bond spreads, and how it interacts with state-level regulatory enforcement. The triple-difference estimator is positive and statistically significant, implying that bond spreads increase for polluting firms located in high regulation states relative to those located in low regulation states following the Paris Agreement. Based on the estimate for β_1 from Equation 9, controlling for regulation, bond spreads do not exhibit a change that is statistically significantly different from zero for top polluting firms located in low regulation enforcements states. Based on the estimate of β_4 from Equation 9, bond spreads increased by about 60 bp for top polluting firms relative to other firms for those firms located in high regulation states compared to those located in low regulation states. This effect is robust to the inclusion of security fixed effects.

The results in Table VII imply that much of the impact of the Paris Agreement on firm cost of debt is through the channel of regulatory costs, which suggests that both credit rating agencies and bond investors believed the Paris Agreement had a greater impact on cost of debt for issuers located in high-regulation states. This implication would be expected because, as stated previously, the Paris Agreement should have created the expectation of increased future regulation. Any new regulation within the US would most likely be enforced through the states, so the Paris Agreement should affect firms most directly through the channel of enforcement of environmental regulation. Thus, we would expect the Paris Agreement to be more important for bond regulatory risk in states where new regulation is expected to be more strictly enforced and less important in those states where there is not an expectation for strict enforcement. This result is also consistent with previous research that has shown that firms face costs due to environmental regulation in the form of legal and regulatory penalties. (Karpoff et al., 2005).

IV. Differences in Interpretation of Climate Regulatory Risk

In the previous sections we showed that firms facing higher levels of climate regulatory risk are perceived as riskier than those with lower levels of climate regulatory risk. In addition to increasing the level of risk, greater climate regulation makes it more difficult for investors to evaluate future firm cash flows. This difficulty is primarily driven from the uncertainty regarding future consequences for firms from climate change, particularly regarding the implementation of climate

regulations.[23] As a result of this uncertainty, we expect that bond investors would be more likely to disagree about the regulatory risk implications.

To test this hypothesis, we examine the deviation of credit ratings faced by bond issues, measuring the deviation of credit ratings as the absolute value of the difference between the Moody's and S&P ratings. If bond investors (or analysts) disagree on the implications of climate regulatory risk on corporate bonds, we expect to observe larger credit rating deviations between the two rating agencies for those firms facing increased credit risk. We examine this using the same type of difference-in-differences design as in the previous sections. If our hypothesis is correct, the deviations of credit ratings should increase for the less environmentally friendly firms relative to more environmentally friendly firms following the passage of the Paris Agreement. [24]

To test the parallel trends assumption, we run the following regression:

$$\left|Moody's - S\&P_{it}\right| = \sum_{k=-11}^{11} \beta_k[(t = k) * EnvTreat_j] + \gamma_i + \kappa_t + \epsilon_{it}, \tag{10}$$

where $|Moody's - S\&P_{it}|$ is the credit rating deviation, the absolute value of the difference between the Moody's rating and the S&P rating for bond issue i at time t. β_k coefficients are plotted in Figure 5. Figure 5a displays results when the treatment used is belonging to a polluting industry and Figure 5b displays results when the treatment used is having a below median environment score. In both cases, bonds issued by firms belonging to the treatment group experienced increasing deviations of credit ratings following the passage of the Paris Agreement relative to those in the control group. The deviations are large and persistent. At the same time, the coefficients are close to zero throughout the entirety of the period prior to December 2015, providing evidence that the parallel trends assumption holds in this context. Next, we run the following difference-in-differences regression:

[23] For instance a Moody's September 9, 2018 ESG methodology report notes "Regulations may set a target... with unclear repurcussions if targets are not met."

[24] Bongaerts et al. (2012) also define credit ratings deviation as the absolute value of the difference between the Moody's and S&P ratings. In unreported tests we use the difference between the Moody's and S&P ratings without taking the absolute value. The results are qualitatively similar, suggesting that Moody's responded more strongly to the Paris Agreement than S&P.

$$\left|Moody's - S\&P_{it}\right| = \beta_1(PollutingIndustry_j * AfterParis_t) + \gamma_i + \kappa_{tp} + \epsilon_{it}. \quad (11)$$

Table VIII displays the results. Columns (1) and (2) show the results when the top polluting industry dummy is used as the treatment variable. The average credit rating deviation for issuers belonging to top polluting industries increased by about 0.22 of a rating relative to other issuers. One interpretation of this result is that for one out of five issuers in top polluting industries, the differential between the Moody's credit rating and the S&P credit rating increased by one notch relative to issuers in other industries following the passage of the Paris Agreement. Columns (3) and (4) show the results when using the below median environment score dummy as the treatment variable. The effect is similar to that observed when examining issuers in top polluting industries. Credit rating deviations for bonds from firms with below median environment scores increased by about 0.24 of a rating relative to bonds from firms with above median environment scores.

Results in previous sections showed that ratings decreased for environmentally unfriendly firms relative to environmentally friendly firms following the passage of the Paris Agreement, implying that credit rating agencies are concerned about climate regulatory risk. However, the results in this section show that these ratings changes differed across the rating agencies. These differences imply that the uncertainty regarding climate regulatory risk actually may have increased following the Paris Agreement.

V. Conclusions

Investors and academics have paid increasing attention to ESG and especially environmental issues over the past several years. In this paper, we provide empirical evidence that suggests uncertainty about future regulatory actions can be a major reason why bond investors respond to firms' environmental performances, and particularly, their exposure to climate risks.

Empirically, we show that being in a top polluting industry is associated with lower credit ratings and higher bond yield-spreads and credit ratings when firms are located in states where they are more likely to be punished for polluting or having poor environmental performance. We

also provide evidence of a causal component to these results by examining bond credit ratings and bond spreads for polluting firms or environmentally irresponsible firms after a shock to regulatory risk, the Paris Agreement. We find that the Paris Agreement appears to have negative consequences for firms that are in top polluting industries or have poor environmental performance in general. More importantly, we find that these negative consequences were stronger in states that enforce regulation more strictly, suggesting that they were stronger because potential new regulations were expected to be enforced more strictly.

These results have important implications for how firms' environmental profiles are related to the issuance and pricing of their corporate bonds. The results imply that bond investors are in fact concerned with issuers' environmental profiles because of potential regulatory costs. That is, if bond investors expect an issuer to be punished for environmentally unfriendly behavior, they are more likely to price those costs into the firms' bonds.

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Figure 1. Google Trend searches related to "Paris climate talks" worldwide from January 1, 2015 until December 31, 2016.

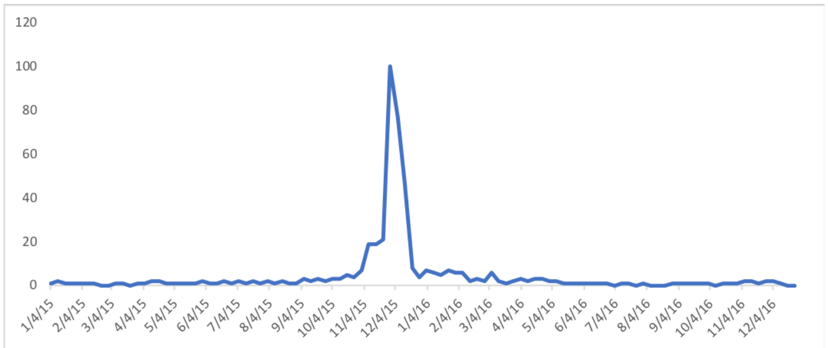
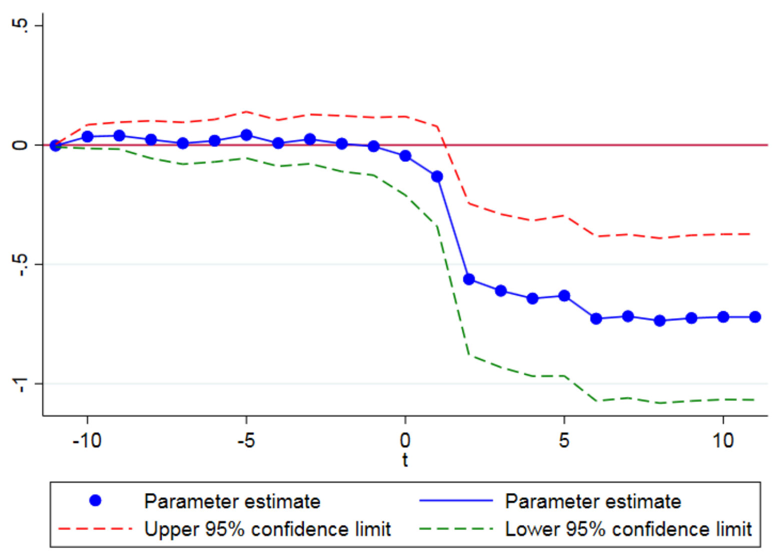


Figure 2. Chart showing regression coefficients from $Rating_{it} = \sum_{k=-11}^{11} \beta_k[(t = k) * EnvTreat_j] + \gamma_i + \kappa_t + \epsilon_{it}$. Pre-period is November 2014 through September 2015 and post-period is December 2015 through November 2016. The chart includes all interaction terms except from November 2014, so the regression coefficient can be interpreted as the impact of belonging to a top polluting industry on bond credit ratings in each period relative to November 2014. (Higher numerical scores indicate better credit ratings.)

(a) $EnvTreat_j = PollutingInd_j$



(b) $EnvTreat_j = BelowMedEnv_j$

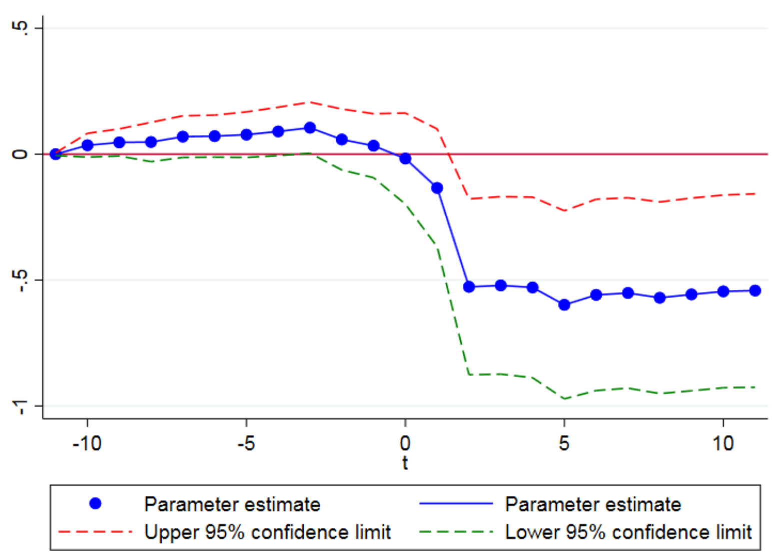
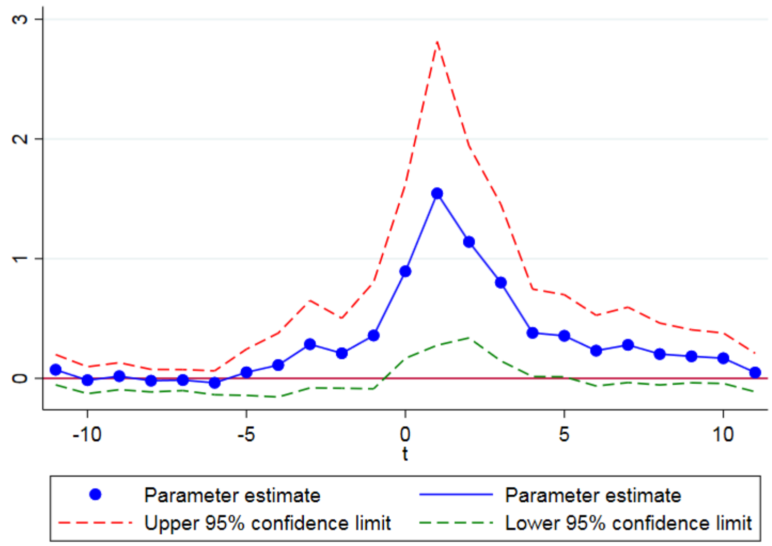


Figure 3. Chart showing regression coefficients from $Spread_{it} = \sum_{k=-11}^{11} \beta_k[(t = k) * EnvTreat_j] + \gamma_i + \kappa_t + \epsilon_{it}$. Pre-period is November 2014 through September 2015 and post-period is December 2015 through November 2016. The chart includes all interaction terms except from November 2014, so the regression coefficient can be interpreted as the impact of belonging to a top polluting industry on bond yield spreads in each period relative to November 2014.

(a) $EnvTreat_j = PollutingInd_j$



(b) $EnvTreat_j = BelowMedEnv_j$

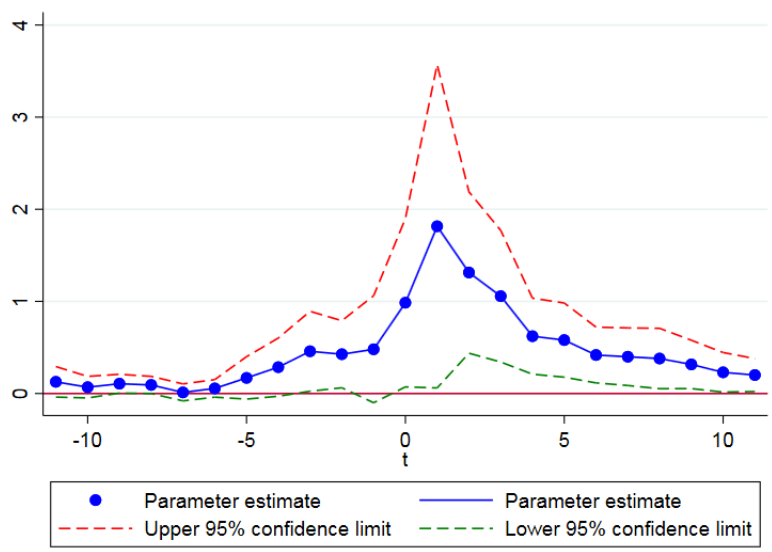
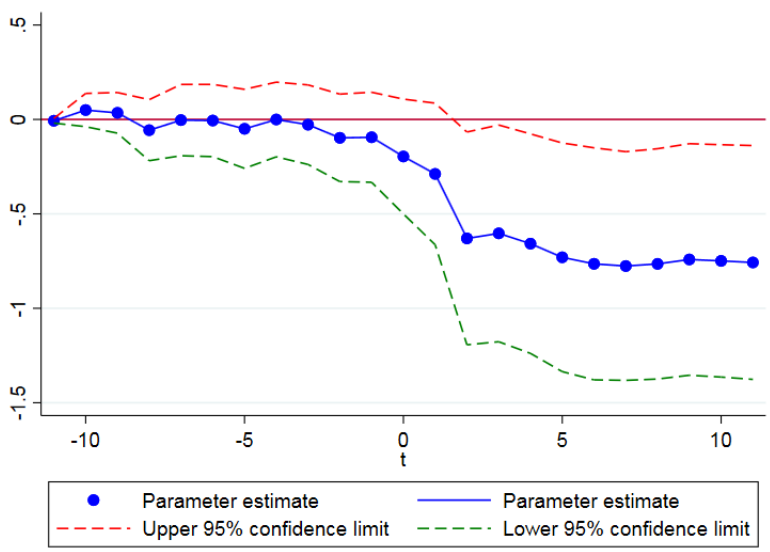


Figure 4. Chart showing regression coefficients $\beta_{k,R,E}$, or the period-by-period triple-difference estimate from $Risk_{it} = \sum_{k=-11}^{11} \beta_{k,E}[(t=k) * EnvTreat_j] + \sum_{k=-11}^{11} \beta_{k,R}[(t=k) * HighReg_j] + \sum_{k=-11}^{11} \beta_{k,R,E}[(t=k) * EnvTreat_j * HighReg_j] + \gamma_i + \kappa_t + \epsilon_{it}$. Pre-period is November 2014 through September 2015 and post-period is December 2015 through November 2016. The chart includes all interaction terms except from November 2014, so the regression coefficient can be interpreted as the impact of belonging to a top polluting industry in a high-regulatory state on bond credit ratings in each period relative to November 2014. (Higher numerical scores indicate better credit ratings.)

(a) $Risk_{it} = Rating_{it}$



(b) $Risk_{it} = Spread_{it}$

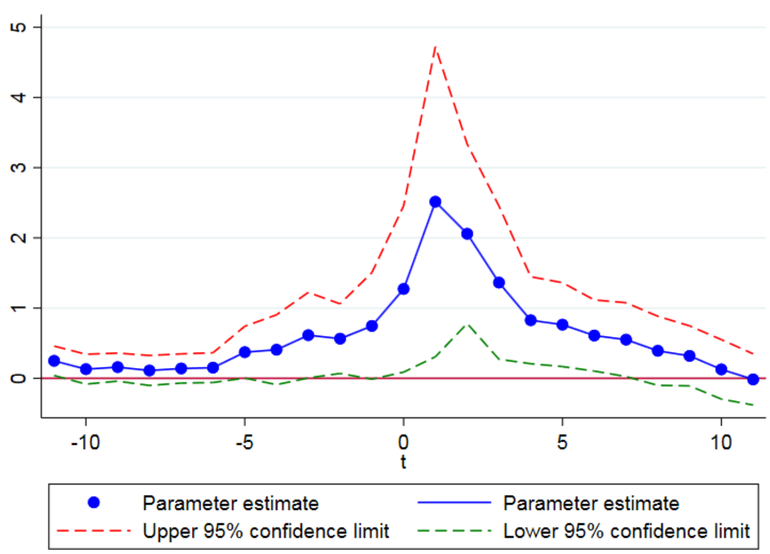
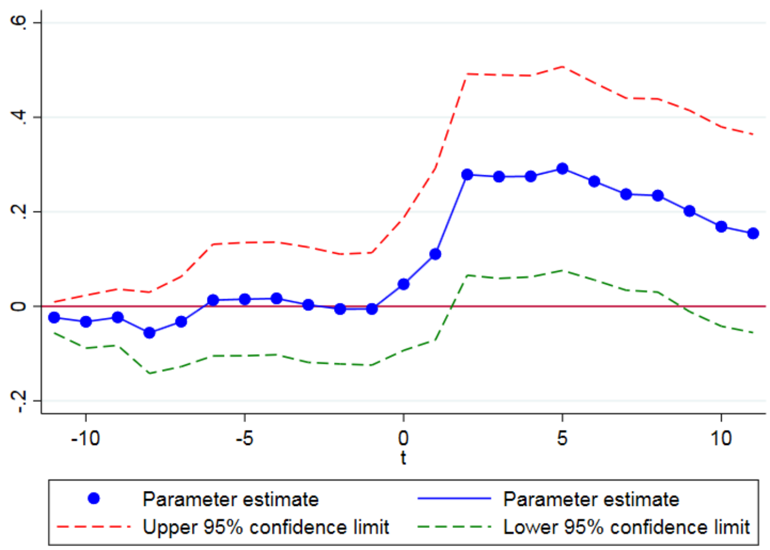


Figure 5. Chart showing regression coefficients from $|Moody's - S\&P|_{it} = \sum_{k=-11}^{11} \beta_k[(t = k) * EnvTreat_j] + \gamma_i + \kappa_t + \epsilon_{it}$. Pre-period is November 2014 through September 2015 and post-period is December 2015 through November 2016. The chart includes all interaction terms except from November 2014, so the regression coefficient can be interpreted as the impact of belonging to a top polluting industry in a high-regulatory state on the absolute value of the difference between the Moody's and S&P rating in each period relative to November 2014. (Higher numerical scores indicate better credit ratings.)

(a) $EnvTreat_j = PollutingInd_j$



(b) $EnvTreat_j = BelowMedEnv_j$

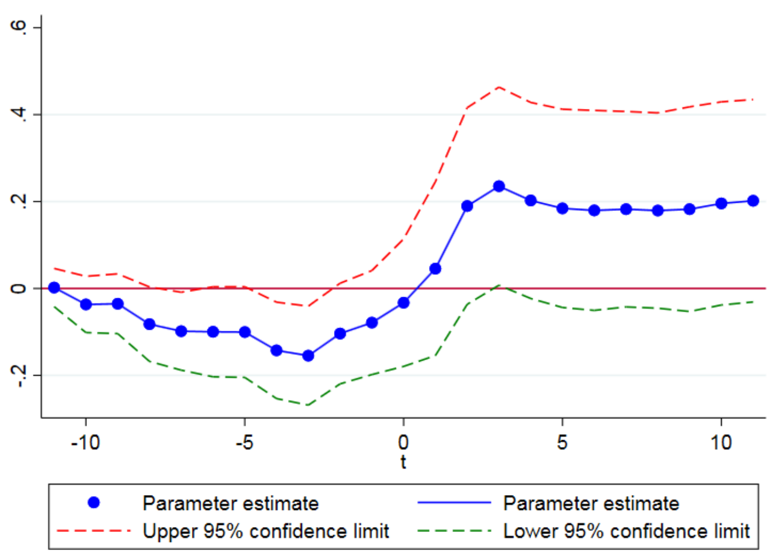


Table I: Summary statistics.

Variable	Units	Mean	Std. Dev.
Security-Year Level Variables			
Annualized Excess Bond Returns	Percent	-1.785	1.03
Spread	Percent	1.662	1.605
Yield	Percent	3.461	2.022
Credit Rating	Rating	14.709	3.027
Time to Maturity	Year	9.622	8.592
Coupon Rt	Percent	5.032	1.933
Ln(1 + Principal Out)	N/A	13.176	.704
At-issue security-year variables			
Offering Spread	Percent	1.489	1.05
Offering Yield	Percent	3.479	1.464
Credit Rating	Rating	15.273	2.815
Ln(1 + Principal Out)	N/A	13.379	.603
Time to Maturity	Year	9.967	7.246
Issuer-Year Level Variables			
Sustainalytics ESG Score	Points	58.304	8.492
Sustainalytics ES Score	Points	55.68	10.266
Sustainalytics Environment Score	Points	54.879	13.172
Polluting Industry	N/A	.411	.492
Pre-tax Interest Coverage	(OIBDP-Int)/Int	.983	.128
Ln(S.D. Returns)	N/A	.919	.303
Profitability	Rev/TA	.227	.179
Leverage	TD/TA	.317	.156
Tangibility	PPE/TA	.331	.263
Annualized Stock Ret	Percent	15.067	96.517
MV Assets	Dollars	1.88e+07	1.82e+07
Ln(Total Assets)	N/A	9.458	1.131
Cash/Assets	Ratio	.1	.109
State-Year Level Variables			
Number Regulatory Enforcements	Enf/Yr	.62	.939
Number Regulatory Inspections	Insp/Yr	.701	.947

Data is from 2009 through June of 2018. Excess bond returns, yield spread, yield, coupon rate, principal amount, profitability, leverage, tangibility, market value of assets and the ln(totalassets) are winsorized at the 1% and 99% levels. The ratings variable is assigned such that a higher number indicates a better rating.

Table II: Credit Ratings and Regulatory Costs.

Col.	(1)	(2)	(3)	(4)
Top Polluting Industry	-0.409		0.240	
	(0.342)		(0.313)	
Environment Scoreˆ		1.121***		0.826***
		(0.174)		(0.145)
State Number of Insp.ˆ	0.712	-0.621		
	(0.796)	(0.492)		
State Number of Pen.ˆ			-0.067	-0.161
			(0.202)	(0.295)
(Top Polluter) * (State Reg. Insp.ˆ)	-1.673**			
	(0.715)			
(Environment scoreˆ) * (State Reg. Insp.ˆ)		1.137***		
		(0.311)		
(Top Polluter) * (State Reg. Enf.ˆ)			-0.307	
			(0.408)	
(Environment Scoreˆ) * (State Reg. Enf.ˆ)				0.600**
				(0.244)
Time to Maturity	0.006	0.005	0.006	0.006
	(0.005)	(0.006)	(0.005)	(0.006)
Leverage	-3.512***	-3.361***	-3.570***	-3.354***
	(1.193)	(1.191)	(1.199)	(1.208)
Pre-tax Interest Coverage	0.032***	0.033***	0.032***	0.033***
	(0.006)	(0.005)	(0.006)	(0.005)
Ln(1 + Principal Out)	0.650***	0.493**	0.658***	0.484**
	(0.172)	(0.207)	(0.169)	(0.208)
Cash/Assets	1.614	0.737	1.569	0.592
	(1.498)	(1.510)	(1.509)	(1.493)
Profitability	0.036	-0.114	0.075	-0.074
	(0.813)	(0.695)	(0.809)	(0.692)
Tangibility	-0.037	0.328	-0.103	0.324
	(0.462)	(0.379)	(0.488)	(0.385)
Annualized Stock Ret	-0.001	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Ln(S.D. Returns)	-3.833***	-3.351***	-3.836***	-3.321***
	(0.444)	(0.334)	(0.446)	(0.334)
Time Fixed Effects	Y	Y	Y	Y
State Fixed Effects	Y	Y	Y	Y
S.E. Cluster	State	State	State	State
Adj. R^2	0.589	0.618	0.587	0.617
Obs	1830	1830	1830	1830

$Rating_{it} = \beta_1 ESGScore_{jt-1} + \beta_2 RegCost_{st-1} + \beta_3 (ESGScore_{jt-1} * RegCost_{st-1}) + \beta_4 X_{it-1} + \kappa_t + \epsilon_{it}$.
All observations are at-issue bonds. All independent variables are lagged except bond characteristics. Environment Scores, coupon rate, leverage, principal outstanding, profitability, annualized stock return, and the standard deviation of stock returns are winsorized at the 1% and 99% levels. *, ** and *** indicate 10%, ** 5% and *** 1% significance respectively. Standard errors are clustered at the firm level. ˆ indicates standardized by mean and scaled by standard deviation.

Table III: Spreads and Regulatory Costs.

Col.	(1)	(2)	(3)	(4)
Top Polluting Industry	-0.005		-0.155**	
	(0.140)		(0.071)	
Environment Scoreˆ		-0.462***		-0.252***
		(0.055)		(0.054)
State Number of Insp.ˆ	-0.277	0.005		
	(0.280)	(0.208)		
State Number of Pen.ˆ			0.010	0.042
			(0.074)	(0.066)
(Top Polluter) * (State Reg. Insp.ˆ)	0.386			
	(0.255)			
(Environment Scoreˆ) * (State Reg. Insp.ˆ)		-0.694***		
		(0.110)		
(Top Polluter) * (State Reg. Enf.ˆ)			0.074	
			(0.092)	
(Environment Scoreˆ) * (State Reg. Enf.ˆ)				-0.272**
				(0.108)
Time to Maturity	0.026***	0.026***	0.026***	0.025***
	(0.003)	(0.003)	(0.003)	(0.003)
Leverage	1.231***	1.256***	1.241***	1.231***
	(0.396)	(0.399)	(0.397)	(0.399)
Pre-tax Interest Coverage	-0.007***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln(1 + Principal Out)	-0.046	-0.005	-0.048	-0.002
	(0.045)	(0.060)	(0.045)	(0.061)
Cash/Assets	-0.213	-0.038	-0.208	0.033
	(0.227)	(0.258)	(0.224)	(0.246)
Profitability	-0.184	-0.047	-0.194	-0.079
	(0.307)	(0.277)	(0.305)	(0.265)
Tangibility	0.111	-0.070	0.123	-0.080
	(0.171)	(0.129)	(0.170)	(0.131)
Annualized Stock Ret	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(S.D. Returns)	1.676***	1.566***	1.677***	1.557***
	(0.191)	(0.147)	(0.192)	(0.147)
Time Fixed Effects	Y	Y	Y	Y
State Fixed Effects	Y	Y	Y	Y
S.E. Cluster	State	State	State	State
Adj. R^2	0.633	0.639	0.634	0.636
Obs	1800	1800	1800	1800

$Spread_{it} = \beta_1 ESGScore_{jt-1} + \beta_2 RegCost_{st-1} + \beta_3 (ESGScore_{jt-1} * RegCost_{st-1}) + \beta_4 X_{it-1} + \kappa_t + \epsilon_{it}$
All observations are at issue bonds. All independent variables except bond characteristics are lagged. Environment Scores, coupon rate, leverage, principal outstanding MV Assets, profitability, annualized stock return, standard deviation of stock returns are winsorized at the 1% and 99% levels. *, ** and *** indicate 10%, ** 5% and *** 1% significance respectively. Standard errors are clustered at the firm level. ˆ indicates standardized by mean and scaled by standard deviation.

Table IV: Change in Credit Ratings after Paris Agreement.

Col.	(1)	(2)	(3)	(4)
Top Polluting Industry	0.475			
	(0.456)			
After Paris*Top Polluting Industry	-0.580***	-0.597***		
	(0.143)	(0.141)		
Low Env. Score			-2.237***	
			(0.387)	
After Paris*Low Env. Score			-0.515***	-0.534***
			(0.160)	(0.159)
Time FE	Y	Y	Y	Y
Security FE	N	Y	N	Y
S.E. Cluster	Firm	Firm	Firm	Firm
Adj. R^2	0.005	0.964	0.154	0.963
Obs	34,734	34,734	34,734	34,734

$Rating_{it} = \beta_1 Env.Treatment_j + \beta_2(AfterParis_t * Env.Treatment_j) + \gamma_i + \kappa_t + \epsilon_{it}$
$PollutingIndustry_j$ is a dummy equal to one if issuer belongs to a top polluting industry. $AfterParis_t$ is a dummy equal to one if observation occurs in December 2015 or later. *, ** and *** indicate 10%, ** 5% and *** 1% significance respectively. Standard errors are clustered at the firm level.

Table V: Summary statistics - Matched Sample.

Group Variable	Unit	**Treatment** Obs	 Mean	 St. Dev.	**Control** Obs	 Mean	 St. Dev.	Diff Mean
Panel 1: Treatment = Top Polluting Industry								
Security-Year Level Variables								
Spread	Percent	2,880	1.574	1.238	2,880	1.369	0.732	-0.205***
Credit Rating	Rating	2,880	15.316	2.659	2,880	15.488	2.638	.172**
Time to Maturity	Year	2,880	9.057	7.924	2,880	9.148	7.942	0.091
Ln(1 + Principal Out)	N/A	2,880	13.373	0.537	2,880	13.412	0.577	.039***
Issuer-Year Level Variables								
Environment Score	Points	795	58.614	12.892	567	62.379	13.526	3.765***
Profitability	Rev/TA	795	0.141	0.092	567	0.177	0.089	.036***
Ln(1 +Total Assets)	N/A	795	10.035	0.979	567	9.901	1.08	-.134**
Leverage	TD/TA	795	0.314	0.116	567	0.317	0.159	0.003
Panel 2: Treatment = Below Med Environment Score								
Security-Year Level Variables								
Spread	Percent	1,848	1.894	1.39	1,848	1.56	0.784	-.334***
Credit Rating	Rating	1,848	14.253	1.888	1,848	14.242	1.863	-.108
Time to Maturity	Year	1,848	7.933	6.385	1,848	7.873	6.423	-.059
Ln(1 + Principal Out)	N/A	1,848	13.239	0.541	1,848	13.179	0.574	-.059***
Firm-Year Level Variables								
Environment Score	Points	637	47.874	6.873	531	66.202	8.557	18.3***
Profitability	Rev/TA	637	0.166	0.111	531	0.172	0.12	0.006
Ln(1 +Total Assets)	N/A	637	9.525	1.023	531	9.6	1	0.074
Leverage	TD/TA	637	0.316	0.108	531	0.314	0.146	-.003

Sample Matched on Environment Treatment in July 2015 (Five months before the Paris Agreement). Summary statistics on the sample are derived from before November 2015 (one month before the Paris Agreement). The sample is formed by using 1 to 1 nearest neighbor Mahalanobis matching on the top polluting industry firms by size, time to maturity, credit rating and the lag of the credit rating in August 2015. Excess bond returns, spread, yield, coupon rate, principal amount, profitability, leverage, tangibility, market value of assets and the ln(totalassets) 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.

Table VI: Change in Yield Spreads after Paris Agreement.

Col.	(1)	(2)	(3)	(4)
Top Polluting Industry	0.205			
	(0.125)			
(After Paris*Top Polluting Industry)	0.434***	0.434***		
	(0.163)	(0.163)		
Low Env. Score			0.334**	
			(0.137)	
After Paris*Low Env. Score			0.503***	0.503***
			(0.176)	(0.176)
Time FE	Y	Y	Y	Y
Security FE	N	Y	N	Y
S.E. Cluster	Firm	Firm	Firm	Firm
Adj. R^2	0.302	0.673	0.413	0.735
Obs	11,520	11,520	7,392	7,392

$Spread_{it} = \beta_1 Env.Treatment_j + \beta_2 (AfterParis_t * Env.Treatment_j) + \gamma_i + \kappa_t + \epsilon_{it}$
$PollutingIndustry_j$ is a dummy equal to one if the issuer belongs to a top polluting industry. $AfterParis_t$ is a dummy equal to one if the observation occurs in December 2015 or later. *, ** and *** indicate 10%, ** 5% and *** 1% significance respectively. Standard errors are clustered at the firm level.

Table VII: Regulatory Risk and the Paris Agreement.

Sample	Full Sample		Matched Sample	
Dep Var	Rating	Rating	Spread	Spread
Col.	(1)	(2)	(3)	(4)
Top Polluter	1.578**		-0.324*	
	(0.703)		(0.175)	
After Paris*Top Polluter	-0.185	-0.212*	0.079	0.079
	(0.132)	(0.125)	(0.108)	(0.108)
High Reg	0.809		-0.190	
	(0.531)		(0.165)	
Top Polluter*High Reg	-1.786*		0.945***	
	(0.924)		(0.301)	
After Paris*High Reg	-0.035	-0.005	0.070	0.070
	(0.093)	(0.089)	(0.144)	(0.144)
After Paris*Top Polluter*High Reg	-0.633**	-0.616**	0.595**	0.595**
	(0.252)	(0.246)	(0.263)	(0.263)
Time FE	Y	Y	Y	Y
Security FE	N	Y	N	Y
S.E. Cluster	Firm	Firm	Firm	Firm
Adj. R^2	0.034	0.965	0.141	0.699
Obs	34,350	34,350	11,520	11,520

$Outcome_{it} = \beta_1 PollutingIndustry_j + \beta_2 HighReg_s + \beta_3(AfterParis_t * PollutingIndustry_j) + \beta_4(AfterParis_t * HighReg_s) + \beta_5(PollutingIndustry_j * HighReg_s) + \beta_6(PollutingIndustry_j * HighReg_s * AfterParis_t) + \gamma_i + \kappa_t + \epsilon_{it}$
$PollutingIndustry_j$ is a dummy equal to one if issuer belongs to a top polluting industry. $AfterParis_t$ is a dummy equal to one if the observation occurs in December 2015 or later. $HighReg_s$ is a dummy equal to one if the issuer is located in above median punishment state in July 2015. *, ** and *** indicate 10%, ** 5% and *** 1% significance respectively. Standard errors are clustered at the firm level.

Table VIII: Difference in Ratings and the Paris Agreement.

Col.	(1)	(2)	(3)	(4)
Top Polluting Industry	0.153			
	(0.111)			
After Paris*Top Polluting Industry	0.227***	0.222***		
	(0.084)	(0.084)		
Low Env. Score			0.059	
			(0.108)	
After Paris*Low Env. Score			0.242**	0.238**
			(0.094)	(0.094)
Time FE	Y	Y	Y	Y
Security FE	N	Y	N	Y
S.E. Cluster	Firm	Firm	Firm	Firm
Adj. R^2	0.034	0.753	0.020	0.753
Obs	33,297	33,297	33,297	33,297

$|Moody's - S\&P|_{it} = \beta_1 Env.Treatment_j + \beta_2 (AfterParis_t * Env.Treatment_j) + \gamma_i + \kappa_t + \epsilon_{it}$
$PollutingIndustry_j$ is a dummy equal to one if issuer belongs to polluting industry. $AfterParis_t$ is a dummy equal to one if observation occurs in December 2015 or later. *, ** and *** indicate 10%, ** 5% and *** 1% significance respectively. Standard errors are clustered at the firm level.