Pricing Climate Change Risk in Corporate Bonds *

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Abstract: Using a firm's geographic footprint to measure its exposure to sea level rise (SLR), I find that corporate bonds bear a climate risk premium upon issuance. A one standard deviation increase in firms' SLR exposure is associated with a 7 basis point premium, representing a 3% increase in average yield spread. This effect is more pronounced for geographically concentrated firms, and within industries vulnerable to extreme weather conditions. I do not find evidence that credit rating agencies account for SLR exposure at bond issuance. Results are robust to placebo tests and inverse propensity weighting to address possible endogeneity.

Keywords: Climate Risk, Corporate Bonds, Sea Level Rise

JEL Classification: Q54, G14, G24 L51

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Introduction

In January 2019, California's largest utility company filed for Chapter 11 in what an article in the Wall Street Journal designated as the "first climate-change bankruptcy" (Gold, 2019). Pacific Gas & Electric's bankruptcy resulted from liabilities created by massive wildfires following an extended period of drought. This climate change bankruptcy will likely not be the last (Macwilliams et al., 2019). Firms are increasingly exposed to physical climate risks including the occurrence of extreme weather events (e.g. hurricanes) and changing climatic conditions (e.g. rising sea levels). As global temperatures rise, droughts, heat waves, floods, cold spells, and other extreme weather events are becoming more severe and frequent, but also more costly. Under a warming scenario of 2°C, economic damage from climate change could reach $69 trillion by the year 2100 (IPCC, 2018).

The growing threat of climate risk is an increasingly important concern for investors. A survey by Krueger et al. (2020) suggests that more than 30% of institutional investors consider physical climate risks relevant for portfolio management decisions today. However, it is unclear whether these considerations are priced in asset valuations. According to a report by the Rhodium Group (2019), the physical risks of climate change are "clear, present and underpriced." Norges Bank Investment management, one of the largest investors funds, concludes that "capital markets do not fully price climate risk" in its 2019 annual Responsibility Report.[1] Corporate disclosure of climate risk by companies is limited (Matsumura et al., 2017), which hinders investors' capacity to estimate the financial implications and magnitudes of these risks. However, policymakers are increasingly aware of the threat that climate change poses for the stability of the financial system (Carney, 2015). Financial markets play a key role in mitigating costly damage from climate change. By pricing climate change risk today, markets can reduce the possibility of wealth transfers between uninformed and sophisticated agents, as well as reduce the future likelihood of extreme price variation (Bernstein et al., 2019).

Empirical evidence relating to the pricing of climate change risk is mixed. In spite of a growing strand of the literature documenting that asset prices, including real estate, equity shares or municipal bonds, account for climate change risks (Bernstein et al., 2019; Kruttli et al., 2019; Painter, 2020), there is also proof of underpricing (Griffin et al., 2019; Bertolotti et al., 2019) and a lack of anticipation of these long-term and

[1] Responsible investment 2019, Norges Bank Investment Management.

highly uncertain risks (Bernstein et al., 2019; Hong et al., 2019). In addition, heterogeneity of climate change beliefs are found to be a significant determinant of real estate prices (Baldauf et al., 2020; Bernstein et al., 2019) and credit spreads of municipal bonds (Goldsmith-Pinkham et al., 2020).

In this paper, I examine whether the corporate bond market prices climate change risk, which refers to the threat of damage, injury, liability, loss, or any other harm that could be caused by climate-related events (Flammer et al., 2019). To my knowledge, it is the first, to assess the importance of climate risk exposure for corporate bond investors. Corporate bonds reflect investors' expectations on future outcomes, which may include their concerns for climate risks. Contrary to stocks, bonds are particularly exposed to large downside risks. Given their payoff profile, the likelihood of large negative shocks is an important factor for prices, which reflect an issuer's capacity to repay its debt (Goldsmith-Pinkham et al., 2020). However, the long run and uncertain nature of climate change risk makes its pricing an unanswered empirical question (Bernstein et al., 2019; Brock and Hansen, 2018).

A challenge in examining corporate climate change exposure, as opposed to municipalities, is that corporations decide where to establish their business. Firms can reduce their exposure to climate change risk by choosing areas less exposed to extreme weather conditions and sea level rise, and can change locations if staying in a given area becomes too costly. However, findings on whether firms actually migrate to safer areas after natural hazards is mixed (Kocornik-Mina et al., 2015; Indaco et al., 2019). In addition, firms can diversify their climate risk exposure by establishing a presence in more than one location, a feature that needs to be considered in light of the potential costs induced by relocation, and the need to be close to networks of customers, suppliers, and investors (Jiang et al., 2019).

To account for the spatial distribution of corporate issuers, I compute weighted measures of physical climate risk exposure based on county-level shares of sales, number of employees, and branches. This allows me to capture the extent of a firm's geographic footprint as well as to account for the possibility that a given firm changes the location of its branches. To measure climate change risk, I focus on the risk of rising sea levels which is a major threat to coastal cities. According to the National Oceanic and Atmospheric Administration (NOAA), global sea levels have risen by about 21–24 centimeters since 1880, and are expected to rise at least 30 centimeters above 2000 levels by the end of the century.[2] However, regions are impacted differently by this

[2]This is equivalent to 8-9 inches since 1880 and 12 inches by the end of century.

rise, depending on local factors such as erosion or ground settling. I exploit regional variation in sea level rise (SLR) exposure by using local measures of expected mean annual losses from sea level rise as a percentage of GDP obtained from (Hallegatte et al., 2013). These estimated losses, which are computed for coastal cities, are based on an expected 40 cm rise of sea levels in 2050. Following Painter (2020), I obtain county-level exposure to sea level rise by mapping cities to counties, and assigning zero to counties with no expected loss.

To assess whether bondholders price climate change risk, I first examine the effect of firms' sea level rise exposure on bond yields and credit ratings at issuance. Focusing on a sample of 6,286 bonds issued by 874 U.S. public firms between 2010 and 2018, I find that SLR exposure significantly affects yield spreads. The results are qualitatively similar after using alternative weighting schemes in calculating SLR exposure. A one standard deviation increase in sales-weighted exposure to sea level rise is associated with a 7 basis points increase in yield spread, equivalent to a 3% increase of average yield spreads, after controlling for key determinants of bond prices (maturity, credit rating, amount issued), issuer characteristics, as well as including year and industry fixed effects. In addition, I find that credit ratings do not appear to capture climate change risk at issuance. These results corroborate anecdotal evidence suggesting that credit agencies are slow to account for these risks (Flavelle, 2019). In particular, a report by the Center for International Environmental Law (CIEL, 2015) alerts on the possibility of a repeated global credit crisis if credit rating agencies continue to miscalculate climate change risk.

The effect of SLR exposure on bond yields holds in a variety of robustness tests, such as excluding bond issuers located exclusively in coastal counties assigned a zero SLR exposure and firms exclusively present inland. To address concerns regarding spurious correlations, I conduct a placebo test which assigns SLR exposure to either neighboring inland counties that are likely to face similar economic conditions, and to matched counties using nearest neighbor propensity matching. The results of this test are negative and insignificant, providing corroborating evidence that SLR exposure is priced in corporate bonds. In addition, I find that the results are not driven by outliers. They are robust to using the natural logarithm of SLR exposure as the dependent variable or a weighed dummy SLR variable where the county-level SLR measure is equal to one if there is sea level risk and zero otherwise.

To address endogeneity bias that arise from the non-random choice of firm location, I re-estimate baseline regressions after applying inverse probability weights. This allows to mitigate concerns that economic and demographic county-level conditions are driving the results by modeling the choice of firms to locate their branches in coastal areas prone to sea level rise. I find that the results hold after applying inverse propensity weighting, with propensity scores obtained from a logit regression relating the probability of having above-median levels of SLR exposure with bond characteristics, issuer characteristics, and county-level economic variables such as GDP per capita, unemployment, population, education, income and default rates.

I next examine the role of spatial dispersion as captured by the number of U.S. counties in which a firm is located. Although some firms are located in a single area, others have branches in more than 2,000 different counties. I first verify whether the effects of SLR exposure are not driven by firms highly spatially diversified by excluding those in the top decile of spatial distribution, with a presence in over 802 counties. The estimated effects on yield spreads are lower for firms less geographically diversified, as well as statistically significant. I then examine the effect separately for firms with low and high levels of spatial dispersion. I find a positive and significant effect of SLR exposure on yield spreads for firms that are geographically less spread-out throughout the US, but no effect for firms with above-median levels of spatial dispersion. The results are similar when using an alternative measure of spatial dispersion, a firm-level Herfindahl-Hirschman index computed as the annual squared sum of county-level sales market-share, that better accounts for firm size. Overall, these results indicate that geographic diversification at the branch level mitigates the cost of climate change risk.

I also examine whether the cost of climate risk is driven by industries vulnerable to floods and extreme weather conditions, either because they rely on physical assets or involve activities that are dependent on good weather conditions. I find that the results are concentrated in such industries, and in particular for firms in the Energy sector. Finally, I find that investors price climate risk in bonds with maturities ranging from 0 to 10 years, consistent with the findings of Krueger et al. (2020) that a majority of institutional investors believe that climate risks will materialize in less than 10 years.

This study contributes to the growing literature examining the role of financial markets in pricing climate change risk by focusing on a key market for U.S. firms and investors: the U.S. corporate bond market. More than double the size of the municipal bond market, it is the primary source of financing for U.S. firms (Bhojraj and Sengupta, 2003), much larger than the stock market.[3] In addition, corporate bondholders bear

[3] According to S&P Global, outstanding U.S. corporate debt instruments rated by S&P Global Ratings amount to $9.3 trillion as of Jan. 1, 2019, whereas the municipal market is approximately $3.8 trillion.

substantially more default risk than municipal bondholders (Moody's, 2017).[4] Given that corporate climate risks are fundamentally downside risks, accounting for these risks is a key concern for investors. My findings complement the work of Painter (2020) and Goldsmith-Pinkham et al. (2020), who show that SLR is priced in municipal bonds.

I also contribute to the nascent literature on the financial consequences of climate risk for firms (e.g., Addoum et al., 2019; Huang et al., 2018; Hugon and Law, 2019; Pankratz et al., 2019; Hong et al., 2019). In particular, contrary to Jiang et al. (2019), I examine SLR exposure at the branch level rather than solely at headquarters, allowing me to capture a fuller picture of corporate SLR exposure. Jiang et al. (2019) find that firms located in areas with higher SLR exposure are penalized when taking out long-term loans: a one standard deviation increase in HQ sea level rise is associated with an additional 4.3 basis points loan spread. Similarly, I find that firms pay bondholders a 4 basis points yield spread premium for an additional standard deviation of SLR exposure. These results have important implications for firms' choice in establishing branches in locations more or less exposed to sea level rise, and wishing to cut down their cost of debt.

Finally, this study adds to the extensive literature on the determinants of corporate bond issuance costs (e.g., Flannery et al., 2012). It relates to Amiraslani et al. (2017) and Jiraporn et al. (2014) which find that a firm's environmental performance is viewed positively by bondholders and improves credit ratings. It also complements the work of Seltzer et al. (2020) which find that corporate bond prices are determined by climate regulatory risks and firms' environmental profiles. In contrast to these papers, I focus on firms' climate change risk as opposed to firms' environmental footprint, as captured by environmental, social and governance (ESG) scores. Firms across all industries and countries are exposed to climate change risk regardless of their emission levels and contribution to global warming. ESG scores, on the other hand, reflect an externality cost driven by corporate behavior, such as a firm's carbon footprint or use of resources.

The rest of the paper is organized as follows. Section 1 reviews the existing literature and describes the motivation for examining whether corporate bondholders price climate change risk. Section 2 describes the empirical setting, specifying how climate change risk is measured based on branch location and county exposure to sea level rise. Section 3 presents the main results and conducts a series of robustness tests. Before concluding, section 4 considers the impact of spatial dispersion, industry heterogeneity, and investors' risk

[4]The five-year municipal default rate since 2007 was 0.15%, whereas the five-year global corporate default rate was 6.92% since 2007.

horizon on the SLR and bond pricing relationship.

1. Pricing Climate Change

Institutional investors believe that climate risks have significant financial implications for portfolio firms (Krueger et al., 2020). Their financial materiality is regarded as being somewhere between "important" and "fairly important". Physical climate risks, i.e. direct costs resulting from changes in the climate, are ranked highest in term of materiality, followed by transition risks, which include regulatory risk (i.e., the cost of new policies such as limited carbon emissions), and technological risks (i.e., the threat of technological disruptions). In addition, climate change has been a top sustainability shareholder proposal in recent years, with increasing shareholder support and approval rates (Flammer, 2015; Flammer et al., 2019).

A growing literature focusing on the financial consequences of climate risk corroborates survey responses and shareholder proposals by providence further evidence on the financial materiality of climate risk. Addoum et al. (2019) find that extreme temperature impacts earnings in over 40% of industries in the U.S., in line with Huang et al. (2018). Exploiting regional temperature variation around corporate headquarters, Hugon and Law (2019) find that a one degree Celsius increase in temperature is associated with a $1.6 million decrease in earnings for a median-sized firm. Pankratz et al. (2019) show that increasing exposure to high temperature and floods reduces revenues and operating income, while Hong et al. (2019) predict poor profit growth for food companies in countries vulnerable to long-term drought.

However, evidence relating to the pricing of climate risk in financial assets is mixed even though recent asset pricing models highlight the importance of climate risks as a long-run risk factor. Bansal et al. (2019) argue that if rising temperature has a long-run impact on the aggregate economy, it should be reflected in current equity prices. Forward-looking capital markets are important to mitigate the impact and cost of climate change but they suffer from the challenges posed by modeling uncertainty Brock and Hansen (2018).

Focusing on the real estate market, Bernstein et al. (2019) find that homes exposed to sea level rise sell at a discount, contrary to Murfin and Spiegel (2020) which find limited price effects. Baldauf et al. (2020) argue that the effect of sea level rise on house prices depends on beliefs about climate change. Beliefs are also found to affect loan officers' mortgage lending decisions, especially in counties heavily exposed to the risk of sea level rise (Duan and Li, 2019).

Examining equity markets, Hong et al. (2019) show that they do not anticipate the effects of predictable worsening drought conditions on food companies until they materialize, while Kruttli et al. (2019) find that extreme weather is reflected in stock and option market prices. Griffin et al. (2019) demonstrate that equity markets recognize but underprice physical climate risk, consistent with forming biased expectations of future equity returns. This is consistent with Bertolotti et al. (2019), which show that the physical climate risks of 269 publicly listed U.S. utilities, based on the physical location of their plants, property and equipment, are underpriced in equity markets.

Municipal bond investors in the U.S. are also aware of the risks posed by climate change (Nauman, 2020). Painter (2020) finds that long-term municipal bonds include the cost of climate change risks, whereas Goldsmith-Pinkham et al. (2020) observe evidence of pricing as of 2011 across bond maturities. Contrary to municipalities, firms have the possibility to relocate and reduce exposure to sea level rise. Jiang et al. (2019) show that firms' cost of long term loans is affected by sea level rise exposure, especially for firms which cannot easily relocate or diversify their SLR exposure. However, Delis et al. (2019) find that banks price climate policy exposure, i.e. transition risk measured as a relative measure of firm-level fossil fuel reserves, only after 2015. In addition, Huynh and Xia (2020) show some evidence that climate change news risk is priced in secondary market bond prices between 2002 and 2016.

In their climate finance review, Giglio et al. (2020) put forward the existence of various ways to measure climate change risk. While some authors focus on physical climate risk (Painter, 2020; Jiang et al., 2019), others have focused on regulatory risk (Seltzer et al., 2020)) or transition risk (Delis et al., 2019). In addition, using machine learning techniques, Sautner et al. (2020) construct a firm-level climate change exposure measure that derives from conversations that take place in company earnings conference calls.

The object of this paper is to examine whether bondholders price physical climate change risk. Bond prices reflect investors' expectations of future outcomes, including potentially long-run and uncertain risks such as climate risks. Given the importance of physical climate risks for investors, I hypothesize that corporate bonds are issued at a premium to account for the future economic cost of sea level rise. By choosing the location of their branches, firms are exposed heterogeneously to the rise of sea levels. Higher SLR exposure leads to a higher risk of value-destructive flooding and storm surges, which in turn increases probabilities of default, a risk born by corporate bondholders.

Firms, contrary to cities, have the possibility to "run-away" from climate risk (Jiang et al., 2019) by either relocating or diversifying their risk. Given that my setting accounts for changes in branch locations, I examine the choice of firms to locate in multiple counties, thereby diversifying their SLR exposure. In particular, I hypothesize that higher spatial diversification will reduce the cost of SLR risk. In addition, certain business activities are more impacted by weather and climate change than others. Extreme weather events can either damage assets thereby reducing corporate profitability, or disrupt business operations which may lead to operating losses. I therefore hypothesize that investors will require a higher yield spread for firms in industries vulnerable to extreme weather conditions (Huang et al., 2018), such as energy, healthcare, utilities, agriculture, food manufacturing and transportation.

Although sea level rise is by essence a long-term risk, Goldsmith-Pinkham et al. (2020) argue that SLR exposure can affect credit spreads through the short-run risk of flooding due to more severe storms. The authors find that SLR is priced in municipal bonds across maturities starting at the end of 2011. In contrast, Painter (2020) finds that SLR exposure is solely priced in bonds with long-term maturities, as early as 2007. Given that a majority institutional investors believe that climate risks will materialize in less than 10 years, I hypothesize that corporate SLR exposure is priced in bonds with maturities in line with these beliefs.

I also verify whether credit rating agencies incorporate SLR exposure when providing bond ratings at issuance. Although there is evidence that credit ratings are lower for firms with poor environmental performance and with high regulatory risk (Seltzer et al., 2020), it is unclear whether credit rating agencies adequately capture physical climate risk. In particular, while there is evidence that firms' carbon footprint increases credit risk (Capasso et al., 2020), there is no evidence yet linking SLR exposure and credit risk. In addition, anecdotal evidence suggests that the interest of credit rating agencies for climate change risk is relatively recent. I therefore hypothesize that SLR exposure will not affect at-issue credit ratings.

2. Empirical Setting

In this section, I describe the data sources and methodology used to construct a sample of 6,286 U.S. corporate bonds issued between 2010 and 2018. I then describe how I obtain issuer sea level rise exposures based on corporate geographic location, before providing key summary statistics.

2.1. Corporate Bonds and Issuer Characteristics

Corporate bond data is obtained from the Mergent fixed income securities database (FISD), which is a comprehensive data source for U.S. corporate bond issues. FISD provides issue dates, yields, prices, bond maturities, coupon rates, amounts issued, and credit ratings. I obtain all bonds issued between 2010 and 2018 for which the issuer's country of domicile is the U.S., excluding non-standard corporate bonds (e.g. convertible or Yankee bonds) and keeping solely bonds with fixed coupons. Yield spreads are obtained by matching each bond to U.S. treasury bonds with similar maturities. For this purpose, I obtain monthly treasury bond data from the Federal Reserve (FRB H15 release) for maturities of 1 month, 3 month, 6 month, 1 year, 2 years, 3 years, 5 years, 7 years, 10 years, 20 years and 30 years. Matching bond yields are obtained by interpolating yields in between each year bracket. Bonds with negative yields are removed from the sample. Credit ratings are transformed to numerical values by assigning each rating to a number ranging from 1, for the lowest rating (D), to 22 for the highest rating (AAA). The primary source of credit ratings is S&P. If it is unavailable, I use ratings from Moody's or Fitch.

Bond issues are merged with Compustat, first by matching the first six digit CUSIP identifiers, and second, by matching names of corporate entities using fuzzy matching and manual matching. Compustat provides balance sheet data for public companies allowing for the construction of issuer-year level variables including size, leverage, return on assets (ROA), market-to-book (MtB), and the share of property, plants and equipment to total assets (PPE).

2.2. Measuring Climate Change Risk

Rising sea levels is a critical consequence of climate change and global warming. As ocean temperatures rise, water expands, and as air temperature increases, melting of ice land such as glaciers adds water to the oceans. According to the NOAA, global mean sea level in 2018 was 8.1 centimeters (3.2 inches) above the 1993 average, and sea levels continue to rise at a rate of about one-eighth of an inch per year.

In the U.S., almost 40% of the population lives in relatively high population-density coastal areas, where sea level plays a role in flooding, shoreline erosion, and hazards from storms. Rising seas threaten infrastructure necessary for local jobs and regional industries by increasing coastal flood risk. Nuisance flooding, which is disruptive and expensive for local economies albeit not dangerous, is 2 to 9 times more frequent than it was 50 years ago. In addition, higher water levels mean that sever storms, such as Hurricane Katrina that hit the Gulf Coast in August 2005, push farther inland and become a larger threat for coastal economies.

Sea levels will continue to rise with global warming, but it is unclear by how much. Future sea level depend on the rate of future carbon dioxide emissions and temperature rise, as well as on the melting rate of glaciers and ice sheets. According to Sweet et al. (2017), global mean sea level is likely to rise 30 centimeters above 2000 levels before the end of the century, even if greenhouse gas emissions follow a relatively low pathway in coming decades. Scenarios with highest greenhouse gas emissions predict sea level rise could be as high as 2.5 meters above 2000 levels by 2100. Others, such as Hansen et al. (2015), predict that end-of-century sea level rise will be negligible.

Furthermore, there is regional variation in terms of sea level rise exposure due to geographic factors, such as where ice is melting or whether tectonic movements cause land to rise or sink. In the U.S., the fastest rates of sea level rise are occurring in the Gulf of Mexico from the mouth of the Mississippi westward, followed by the mid-Atlantic. Sweet et al. (2017) expect sea level rise along the coasts of the U.S. Northeast to be greater than the global average. Krasting et al. (2016) point out the vulnerability of the U.S. east coast to near-future sea level rise.

In this paper, I use county-level measures of expected economic losses from sea level rise following Painter (2020). SLR captures potential economic damage stemming from climate-induced sea level rise. Focusing on major coastal cities, it is equal to the expected mean annual loss from sea level rise as a percentage of city GDP. Estimated losses are predicted by Hallegatte et al. (2013) based on a 40 cm rise in sea level in 2050. County-level losses are obtained by mapping cities to counties. Inland counties and coastal counties for which there is no predicted estimate of losses are assigned a risk of zero (Figure 1).

[Figure 1 about here]

Table 3 ranks cities (and counties) from highest to lowest exposure to sea level rise. SLR is highest in Orleans Parish, where a rise of 40 cm of sea levels in 2050 is predicted to cause losses of 1.479% of GDP. Santa Clara, CA, is the coastal county with the least expected loss due to rising sea levels (0.001%).

[Table 2 about here]

2.3. Determining Corporate Geographic Location

To determine a firm's geographic footprint, I obtain information on the location of establishments, as recorded in Infogroup's Historical Business Database, available in WRDS. Infogroup gathers location-related business data from various public data sources such as local yellow pages, white page directories, credit card billing statements, and public records. They also makes phone calls to update data on establishments, such as the number of full-time equivalent employees. Branch-level data allows to gauge the geographic distribution of firm's operation (Barrot and Sauvagnat, 2016; Pan et al., 2019; Yang, 2018; Baker et al., 2020). Parent companies from Infogroup are matched by name to the merged Compustat-FISD sample of firms, which allows the identification of branch locations for each issuer.

I first aggregate information on sales, employees, and the number of branches each year to the issuer-county level. I then calculate the fraction of a firm's sales, employees and branches in a given county. A firm-year climate change risk measure, $SLR_{i,t}$, is obtained by applying these weights to the sea level rise exposure associated with the county where at least one branch is located, as follows:

$$SLR_{i,t} = \sum_{c=1}^{C} Weight_{i,t,c} * SLR_c \tag{1}$$

where $Weight_{i,c,t}$ is either the fraction of sales, employees or branches, i is the bond issuer, c is the county where the issuer is located, and t is the year of reporting. Bond issuers have branches located in 3,117 counties across the U.S., with some firms more geographically diversified than others. On average, firms have branches located in 251 different counties (Table 3).

I also identify the state and county of corporate headquarters (HQ) from SEC filings using 10-X header data[5]. This data is made available from 1994-2018 by the Notre Dame Software Repository for Accounting and Finance (SRAF)[6]. Corporate headquarters are included in Infogroup and account for 60% of employees on average (Barrot and Sauvagnat, 2016).

Corporate bond issuers are headquartered in 227 different counties, with a majority of firms located in New York County. Some firms change their headquarters' location. For example, General Electric moved from Fairfield, Connecticut to Boston, Massachusetts, in 2016 . Among the firms in the sample, only 3% (28 firms among 874) changed their headquarters' location between 2010-2018.

2.4. Summary Statistics

The final sample constitutes of 6,286 bonds issued by 874 distinct public companies, between 2010 and 2018. Summary statistics are reported in Table 3 Panel A. Average yield spreads are 2.3%, although they vary substantially, with a standard deviation of 2.8%. On average, offering yields are 4.4% and equivalent treasury bond yields are equal to 2.1%. Bonds included in the sample have ratings ranging from CCC- to

[5]Data on HQs can also be obtained from Compustat. However, while it reports the address of a firm's current HQ location, it back-fills this information for previous years, and does not control for HQ relocations.

[6]https://sraf.nd.edu/data/augmented-10-x-header-data/

AAA, and are rated BBB+ on average. Bonds' average maturity is 11 years and investors receive a 4.4% fixed coupon. The average issuer has assets equal to $340 billion, a return on assets of 4% annually, holds 37.1% of debts relative to total assets, and has a market-to-book ratio of 1.6. The companies included in the sample invest in material assets and hold on average 22% of their total assets in property, plants and equipment.

[Table 3 about here]

Average sales-weighted SLR for bond issuers is 0.016%, ranging from 0 to 1.434%. Weighing by number of employees or branches provides similar SLR exposure (i.e. 0.018% and 0.0168%). All measures capture important variation in geographic dispersion, with standard deviations ranging between 0.021% and 0.037%. This feature is reflected in the number of counties in which an issuer has branches. On average, a firm is located in 251 different counties, ranging from 1 (Netflix Inc.) to 2,568 (for JP Morgan chase). Geographically concentrated firms have a HHI value of 1, though on average it is equal to 0.2.

Panel B and C of Table 3 provide descriptive statistics for the subsample of Investment grade bonds and High Yield bonds. There are 4,952 bonds with a credit rating above BBB- in Standard & Poor's scale, representing 79% of the sample of bonds. High yield bonds procure on average a higher spread (3.94%) relative to investment grade bonds (1.86%) and have longer maturities (12 years v.s. 7). Maturity distribution for both types of bonds can be found int Table A.1 of the Appendix, Panel B. In addition, issuers of investment grade bonds are on average larger firms, more profitable and less leveraged. They also tend to be more geographically diversified although their SLR exposure is comparable to that of high yield bond issuers.

Correlations are reported in Table 4. SLR exposure measures are positively correlated with yield spreads, suggesting that higher climate change risk may lead to a higher cost of issuance. Sales-weighted SLR is negatively correlated with credit ratings, indicating that higher exposure to climate change risk may reduce the credit quality of an issuer, although employee- and branch-weighted SLR is positively related to credit quality. The three SLR measures are highly positively correlated, ranging from 0.96 for sales and employee weighted measures, to 0.79 for sales and branch weighted measures. Higher geographic dispersion, proxied by the number of counties, is negatively correlated with yield spreads but positively correlated with credit quality, while HHI is positively correlated with yield spreads and negatively correlated with credit ratings. Geographic dispersion is also negatively associated with sea level exposure, as can be expected, as geographic diversification allows attenuating climate risk exposure. Larger and more profitable firms are expected to have a lower cost of debt issues and better quality ratings, whereas increased leverage is associated with a higher cost of debt and lower ratings. Size is highly correlated with credit quality (0.61).

[Table 4 about here]

3. Climate Change Risk and Bond Characteristics at Issuance

In this section, I present the estimation procedure, followed by the main results. I then conduct robustness tests to verify the relation between SLR exposure and yield spreads holds.

3.1. Regression Design

To examine the impact of climate change risk on bond characteristics at issuance, I estimate the following ordinary least squares (OLS) regression focusing on corporate bonds issued from January 2010 to December 2018:

$$BondCharacteristics = \alpha SLR + \beta' \times X + \gamma + \epsilon \tag{2}$$

with $BondCharacteristics$ the yield spread or the credit rating of the bond at issuance; SLR is the branch-level SLR exposure of the bond issuer, weighted either by the number of sales, employees or branches in a given county and year; X is a vector of control variables including bond characteristics (amount issued, maturity, credit rating), firm characteristics (size, ROA, leverage, market-to-book, PPE), as well as county-level economic conditions at the headquarters; γ are year and industry fixed effects. Standard errors are clustered at the issuer level, as the residuals of the regressions could be correlated for repeated issues by a given firm.

To control for county-level local conditions at the firm headquarters, I include $GdpPerCapita$, where GDP in current dollars is obtained from the Bureau of Economic Analysis and population estimates are from the Census Bureau's Population Estimates Program. $Unemployment$ rates ares provided by the U.S. Bureau of Labor Statistics. In addition, to control for unobserved aspects of the U.S. economy as well as common macroeconomic trends, I include year fixed effects. Adding industry fixed effects allows to identify the impact of SLR on bond yields by comparing yields from different companies within a same industry.

Based on prior literature, I expect the parameter of interest, α, to be positive for yield spreads, as investors require higher yields from companies exposed to higher SLR. However, I expect the coefficient to be negative when examining credit ratings, as higher exposure to SLR undermines the credit quality of the issuer.

3.2. Main Results

Table 5 presents the results for the effects of SLR exposure on bond yield spreads. The first column focuses on SLR exposure weighted by the relative sales amount in a given county, while the second and third columns report the effects of SLR exposure weighted by number of employees and branches. SLR exposure significantly impacts yield spreads, in all specifications, although significance is strongest when weighing by sales. Economic magnitudes are larger when weighting by employee and branch shares. Under specification (1), a one percentage point increase of SLR exposure at the branch-level is associated with a 1.8 percentage point increase in yield spreads, significant at the 5% level. In other words, a one standard deviation increase in a firm's sea level exposure (0.037%) is expected to increase yield spreads by 0.07 percentage points, equivalent to a 3% increase of average yield spreads (2.3%). Comparatively, a one notch increase in credit quality is expected to reduce the cost of issuance by 0.13 percentage point, or a one standard deviation increase in credit quality (3 notches) is related to a 0.4 reduction in yields. In line with other findings in the corporate bond literature, I find that issuance costs are lower for large amounts of bonds issued, for smaller maturities and better credit quality. The issuer's profitability is highly significant, indicating that investors require higher yields for less profitable firms. Both market-to-book and leverage are also highly significant, where higher leverage increases the cost of debt while higher growth opportunities reduce yield spreads. Finally, firms with higher shares of property, plant and equipment appear to have lower issuing costs.

[Table 5 about here]

Table 6 reports the effect of sea level rise exposure on credit ratings at issue. Overall, there is no compelling evidence that SLR exposure is accounted for by credit rating agencies at issuance. Focusing on specification (1), an additional percentage point of exposure to SLR predicts lower credit scores by 0.6 notches. The results are, however, not significant. Different weighting schemes provide similar results, although the sign becomes positive for branch-weighted SLR. In addition, improved credit quality is associated with larger firm size and longer maturities. Stronger profitability, growth expectations and lower leverage are significantly associated with better ratings, as expected.

[Table 6 about here]

The results in Table 6 imply that credit rating agencies do not yet consider physical climate risk when evaluating issuers, although they appear to capture regulatory risk (Seltzer et al., 2020). Credit ratings agencies' interest in climate risk is indeed relatively recent. Moody's acquisition of a climate data firm, signaling new scrutiny of climate risks, only dates back to July 2019 (Flavelle, 2019), following the publication of a new methodology to assess environmental, social and governance (ESG) risks published in September 2018 (Moody's, 2018). Overall, as pointed out by the Institute for Energy Economics and Financial analysis (IEEFA, 2019), credit rating agencies have been slow to act on climate change, which corroborates the results found in this study.

3.3. Robustness Analysis

A first concern with the sea level rise exposure measure is that unobserved coastal counties may bias the results associating sea level rise exposure to yield spreads (Painter, 2020). In the baseline specification, all cities (and corresponding counties) for which Hallegatte et al. (2013) do not compute a loss estimate of flood risk are assumed to have a climate risk of zero. Therefore, firms located in coastal counties may be exposed to SLR, even though it is not quantified by this measure. Although this bias probably leads to an under-estimation of the effect of climate risk on bond yields, I address this concern by omitting bonds issued by companies exclusively located in coastal counties with no SLR exposure. I identify coastal counties following the definition provided by the National Oceanic and Atmospheric Administration (NOAA) and identify companies with branches all located in coastal counties not listed in table 2, and exclude from the sample. Table 7 Panel A reports the results for this test, for the three weighted measures of SLR. Both the significance and magnitudes of the SLR effect on bond yields remain unchanged.

[Table 7 about here]

A second concern is that over-exposure to inland counties with no SLR exposure may bias the estimated effect. I therefore verify whether omitting bonds issued by companies exclusively located inland alters the regression results associating SLR exposure and yield spreads. The results of this test are reported in Panel B of Table 7. The magnitude of the effect increases slightly and significance remains at either the 5% or 10% level.

Another potential concern is that the small number of counties for which a measure of SLR is obtained is generating spurious correlation[7]. To address this issue, I conduct a placebo test which replaces exposed counties with inland neighboring counties, similarly to Painter (2020) and Jiang et al. (2019). Neighbor counties are likely to experience similar economic conditions to exposed counties albeit with no risk of sea level rise, given that they are inland. To identify neighbor non-coastal counties, I use county distance.[8] and find the closest county that is not a coastal county. Matched neighbor counties are listed in the Appendix, Table A.3. The results of the placebo test are presented in Table 8. The coefficients for $NeighborSLR$ are no longer significant and are now negative.

In addition, I compare economic conditions of SLR counties and their matched neighbor counties (Table A.4) and find that neighboring inland counties differ in terms of their population size, GDP per capita, unemployment, education and income levels. On average between 2010-2018, coastal SLR counties are richer and more populated, have a higher share of college completion rates and less unemployment. To address these discrepancies, I obtain matched counties with similar economic conditions using nearest neighbor matching (Rubin, 1973). Propensity scores for non-SLR counties are obtained from the estimation of a county-level logit regression, where the dependent variable is the probability that a county is exposed to SLR, and the covariates are the log-transformation of GDP per capita, population and income, as well as levels of unemployment and education. The names of matched counties are listed in the Appendix, Table A.3. Average economic conditions (Table A.4) are closer to those in SLR counties, providing more confidence in the results of the placebo test. As can be seen from Table 8, the coefficients for $MatchedSLR$ are also negative and not significant. Overall, these results provide some evidence that the sea level rise measure is correctly identifying climate risk, rather than picking up unobserved county-specific local traits.

Finally, I verify that the results are not driven by outliers. I first confirm that the effect of SLR exposure on yields spreads remains after log-transforming the key explanatory variable, SLR exposure. Results are presented in the Appendix Table A.2, columns (1)-(3) for SLR weighted by sales, employees, and branches. Second, I replace the county-level SLR exposure ranging from 0.001% to 1.479% by a dummy variable equal to 1 if a county is exposed to SLR, and 0 otherwise. This allows me to construct a weighted DummySLR variable, for which I verify the robustness of the baseline results in columns (4)-(6). Magnitudes increase slightly

[7] Only 37 counties have SLR estimates, as listed in Table 1.

[8] Using the county distance database https://data.nber.org/data/county-distance-database.html

for the sales-weighted variable and reduce for the employee- and branch-weighted variables, but significance remains at the 5% level.

3.4. Inverse Propensity Weighting

In this section, I address endogeneity biases that arise from the non-random choice of branch locations by companies. Potential biases may be related to characteristics of firms as well as to key attributes of the counties where a firm chooses to locate, including demographics, economic conditions, or education levels. I use inverse propensity weighting to alleviate concerns that observable factors are driving baseline results.

Inverse probability of treatment weighting (IPTW) provides unbiased estimates of average treatment effects by using the reciprocal of the estimated propensity for treatment to weigh observation in a sample (Austin and Stuart, 2015). The propensity score is defined as the probability of treatment selection (i.e. the probability that a bond issuer has above median SLR exposure), conditional on observed baseline covariates. Weighting observations creates a synthetic sample in which treatment assignment is independent of measured baseline covariates.

I first separate firms into two groups: those with above median SLR exposure (treatment), and those with below levels of SLR exposure (control). I then estimate propensity scores using a logit model regressing the treatment group dummy on bond characteristics (credit rating, amount issued, bond maturity), issuer characteristics (size, ROA, leverage, market-to-book, PPE), and weighted economic conditions (GDP per capita, unemployment, population, default rates, education and income).

I then run the baseline OLS regression after applying inverse propensity weighting and present the results in Table 9. The magnitudes of the coefficient are similar to those obtained when running the baseline regression, ranging from 1.3 to 5.9, and all three are statistically significant. This test further alleviates concerns of confounding factors that may be driven by the choice of firms to locate their activities on coastal counties, by reducing differences between highly exposed firms and those less exposed to sea level rise.

4. Corporate Heterogeneity and Pricing of Climate Change Risk

In this section I examine the effect of spatial dispersion, industry groups and investment horizon, on the SLR-spread relationship.

4.1. Spatial Dispersion

A challenge when considering corporate exposure to climate change risk, is accounting for spatial dispersion. While some firms are located in a unique county, some have branches located in more than 2,000 different locations. To verify whether highly dispersed firms are not driving the results, I first run the baseline regression by excluding issuers in the top decile of geographic dispersion, proxied by the number of counties in which a firm has branches. More specifically, I exclude issuers that are located in more than 802 counties. Results are reported in Table 10, Panel A. The coefficients of interest remain significant at the 10% level and economic magnitudes are similar although slightly reduced.

To examine the impact of spatial distribution, I separate the sample into two sub-samples: firms with low spatial dispersion (below median number of counties) and firms with high spatial dispersion (above median). Based on the estimations presented in Panel B of Table 10 columns (1)-(3), I find that the effect is positive and significant for firms that are geographically concentrated. Focusing on sales-weighted SLR exposure, the estimates indicate that a one standard deviation increase in SLR exposure leads to a 7 basis point higher yield spread. On the other hand, results in columns (4)-(6) indicate that for geographically dispersed firms, SLR exposure has no significant impact on yield spreads.

As an alternative proxy for spatial dispersion, I compute a firm-level Herfindahl-Hirschman Index as the sum of squared county-level market shares based on branch sales. This measure takes into account the relative size distribution of a firm across the U.S. market based on sales amount at each branch location. It ranges from 0 to 1, a low value indicating high geographical diversity. Geographically concentrated firms have an HHI closer to 1. The results, provided in Table 11, are similar to those observed when using number of counties as the measure of spatial dispersion. I find that the effect is positive and significant for concentrated firms, with above median levels of HHI, whereas as the results are insignificant for spatially diversified firms. Overall, these results suggest that by being geographically dispersed, issuers can diversify their climate risk exposure.

4.2. Industry Heterogeneity

Another specificity of corporate exposure to climate change risk is that it depends on the business type of each firm. Companies located in areas with SLR will be less exposed if their activities have lower chances of being disrupted by floods. For example, Belasen and Polachek (2008) find that the construction and service sectors are positively impacted following a hurricane, while the manufacturing, trade, transportation, and utility, as well as the finance, investment, and real estate industries are negatively affected. In particular, firms with substantial physical or tangible long-term assets (i.e. property, plant, and equipment including buildings, machinery, land, office equipment, furniture, and vehicles) are at higher risk of being impacted by floods and extreme weather conditions. Therefore, baseline regressions include PPE as a control variable.

Huang et al. (2018) identifies industries which are vulnerable to extreme weather conditions in two ways. First, extreme weather conditions can affect corporate profitability by damaging assets (Reisch, 2005), especially for industries with heavy non-deployed and long-lived capital assets which include energy, health-care and utilities (SASB, 2016; Wilbanks et al., 2007; McCarthy et al., 2001). Second, extreme weather events can disrupt business operations and result in operating losses, especially for firms dependent on moderate weather conditions which heavily rely on infrastructure, such as agriculture, food manufacturing, business services, and transportation.

In this section, I examine whether exposure to SLR affects bond yields differently depending on whether the issuer operates in a vulnerable industry or not. Following Huang et al. (2018), I consider agriculture, energy (mining and oil extraction), food products, healthcare, communications and transportation, as industries vulnerable to climate change risk.[9] I create a dummy variable equal to 1 if an issuer is in one of these industries, identified using the Fama-French 48 industry classification, and 0 otherwise.[10] I first examine whether the effect of SLR on yield spreads differ for vulnerable industries, relative to non-vulnerable industries.

As can be seen in Table 12, Panel A, the effect of SLR exposure on the cost of debt issuance seems to be driven by issuers operating in vulnerable industries. Although the coefficient estimates for non-vulnerable industries are positive, significance disappears. Panel B provides an additional breakdown by industry group. The main sector driving the results is Energy (e.g. Phillips 66, Chevron, or Exxon Mobil), which is highly significant. A one standard deviation increase in SLR exposure leads on average to a 3 basis point higher yield spread for firms in that sector. In addition, the coefficient for firms in the Communication industry (e.g. ATT, Verizon, or Time Warner) is positive but not significant, as can be explainex by their above average level of

[9] Following Kling et al. (2019), I exclude business services which are too broad.

[10] Vulnerable Industries is an indicator variable that equals one for Agriculture (Fama–French Industry Code 1), Communication (Code 32), Energy - Mines (Code 28), Coal (Code 29), and Oil (Code 30) -, Food Products (Code 2), Health Care (Code 11), and Transportation (Code 40), and zero otherwise.

spatial diversification (i.e. branch locations in over 700 counties as per Table A.6). For transportation companies (e.g. Delta airlines or Expedia), SLR exposure is associated with a reduction of yield spreads, which may be explained by a relatively high degree of spatial diversification compared to companies in the Energy sector (on average located in 230 counties vs 177 as per Table A.6 in the Appendix). Finally, a high concentration of agriculture and food companies located inland (76% of their branches vs 66% for all companies) may explain their overall lower SLR exposure and therefore a non-significant effect on bond yield spreads.

[Table 12 about here]

Overall, these industry-specific result provide additional evidence supporting the link between SLR exposure and the cost of corporate bond issuance, but show notable industry heterogeneity.

4.3. Investor Horizons

An important challenge for investors when considering climate change risk is the uncertainty of the time horizon in which these risks are likely to materialize (Barnett et al., 2020). According to institutional investors surveyed by Krueger et al. (2020), fewer than 10% believe that climate risks will materialize only in 10 years or more. Among the 401 respondents, 34% believe that physical climate risks have already materialized today. However, when examining the period ranging from January 2004 and March 2017, Painter (2020) finds that investors price climate change risk in long-term municipal bonds (i.e. with maturities greater than 25 years).

To examine the role of investment horizon for bonds issued between January 2010 and December 2018, I separate my sample of bonds into four categories based on bond maturities, and examine the effect of sea level rise exposure on yield spreads. The results reported in Table 13 indicate that excess cost resulting from SLR exposure is driven by bonds with maturities ranging from 0 to 10 years. Contrary to Painter (2020), I do not find a significant effect for bonds with maturities above 10 years. The discrepancy of results may however stem from a differing sample period, as my focus is on bonds issued between 2010 and 2018. In addition, these results seem in line with the survey responses collected by (Krueger et al., 2020).

[Table 13 about here]

Overall, the evidence relayed in the previous sections suggests that firms located in counties with sea level rise exposure pay a premium when issuing bonds with maturities ranging from 0-10 years. This effect is particularly important for vulnerable industries in the Energy sector. Spatial diversification allows to mitigate this effect, which is stronger for firms present in less counties or with branches located in majority inland.

Conclusion

This study provides empirical evidence on the pricing of physical climate risk in U.S. corporate bonds. I find that investors require a premium for bonds issued by firms exposed to sea level rise, especially those with activities identified as vulnerable to floods and extreme weather events (e.g. Energy sector), less geographically diversified across the U.S., and which issue bonds with maturities ranging from 0 to 10 years. In addition, I find no evidence that sea level rise exposure is accounted for in credit ratings at issuance, supporting anecdotal evidence that credit rating agencies are not adequately taking into account physical climate risk.

Although prior research has shown the importance of firms' regulatory risk for investors, this paper is the first to examine how physical climate change risk impacts corporate fixed income assets and their ratings at issuance. Importantly, by capturing sea level rise exposure at the branch level, I obtain a fuller view of corporate SLR exposure than by focusing solely on firms' HQ location.

The evidence found in this study has important implications for firms considering where to locate branches in the U.S., in particular those vulnerable to floods and extreme weather events. Reducing exposure to sea level rise appears to be a way to mitigate the cost of issuing debt, as well as spatially diversifying locations. In addition, this study finds support for an inadequate account of climate change risk in at-issue credit ratings, a warning for policymakers concerned with financial stability and the risk of a future climate credit crunch.

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Figure 1: Counties Exposed to Sea Level Rise

This Figure presents counties exposed to sea level rise, as computed by (Hallegatte et al., 2013). Expected mean annual losses as a percentage of a city's GDP are obtained assuming a 40 cm rise in the sea level as of 2050 and that cities attempt to adapt to this rise. Cities are then mapped to counties following (Painter, 2020). All counties for which there is no measure computed by (Hallegatte et al., 2013) are assigned a SLR of zero.

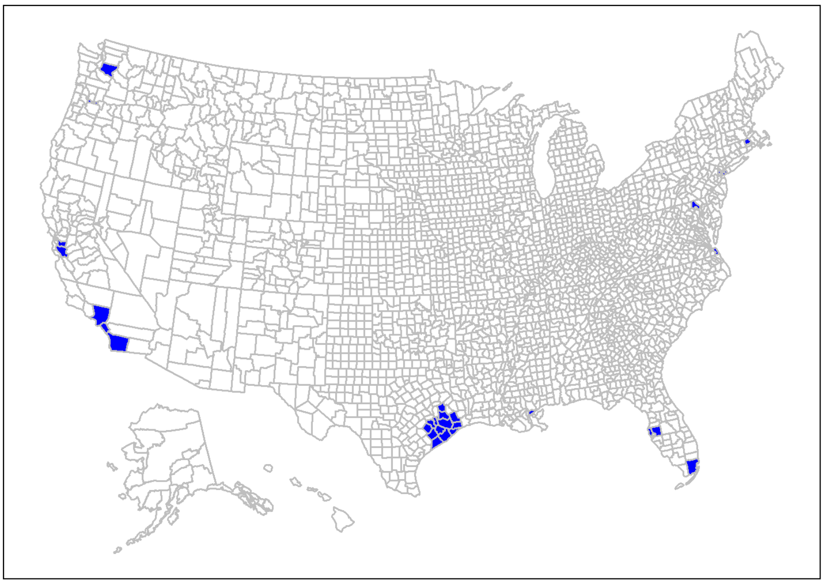

Table 1: Variables and Data Sources

Variable	Definition	Data Source
	A: At-issue Bond Level variables	
$\text{YieldSpread}_{i,t}$	Bond i's yield spread at issue in year-month t. It is equal to the difference between bond i's offering yield and the yield of a treasury bond with similar maturities. It is expressed in percentage.	FISD Mergent
$\text{CreditRating}_{i,t}$	The credit rating of bond i issued in year-month t. Credit ratings are transformed to numerical values such that the lowest rating is equal to 1 (D), and the highest is equal to 22 (equivalent to AAA). Credit ratings are either provided by S&P, Moody's or Fitch, in this order of availability.	FISD Mergent
$\text{OfferingYield}_{i,t}$	Bond i's offering yield at issue in year-month t, expressed in percentage.	FISD Mergent
$\text{OfferingPrice}_{i,t}$	Bond i's offering price at issue in year-month t, expressed in percentage.	FISD Mergent
$\text{Maturity}_{i,t}$	Bond i's maturity at issue in year-month t, expressed in years.	FISD Mergent
$\text{Amount}_{i,t}$	Bond i's amount issued in year-month t, expressed in log of the dollar amount.	FISD Mergent
	B: Issuer Level Variables	
$\text{Size}_{j,t}$	The size of issuer j in year t, expressed in log of the dollar amount of total assets (at).	Compustat
$\text{ROA}_{j,t}$	The return on assets of issuer j in year t. It is computed as the ratio of net income (ni) on total assets (at).	Compustat
$\text{Leverage}_{j,t}$	The leverage of issuer j in year t, computed as the sum of long term debt (dltt) and current debt (dlc) divided by total assets (at).	Compustat
$\text{MtB}_{j,t}$	The market-to-book value of issuer j in year t. It is obtained as follows: $(at - seq + csho * prcc_f)/at$	Compustat
$\text{PPE}_{j,t}$	The ratio of property plant and equipment (ppent) to total assets (at), of issuer j in year t.	Compustat
$\text{SLR\_Sales}_{j,t}$	The weighted-average sea level rise exposure of issuer j in year t, based on sales weights and issuer's geographic presence in the U.S.	Infogroup and (Hallegatte et al., 2013)
$\text{SLR\_Employ}_{j,t}$	The weighted-average sea level rise exposure of issuer j in year t, based on the fraction of employee and issuer's geographic presence in the U.S.	Infogroup and (Hallegatte et al., 2013)
$\text{SLR\_Branch}_{j,t}$	The weighted-average sea level rise exposure of issuer j in year t, based on relative number of branches and issuer's geographic presence in the U.S.	Infogroup and (Hallegatte et al., 2013)
$\text{NbrCounties}_{j,t}$	The number of U.S. counties in which issuer j is located in year t.	Infogroup
$\text{HHI\_Sales}_{j,t}$	A Herfindahl-Hirschman index obtained for issuer j in year t, computed as the sum of squared county-level market shares based on branch sales, indicating the level of spatial diversification of the firm. A score close to 0 signals high spatial diversification whereas a score of 1 suggests low spatial diversification.	Infogroup
$\text{Inland}_{j,t}$	Inland captures the percentage of branches located inland for issur j in year t. Inland counties are those that are not identified as coastal counties by the NOAA.	Infogroup and NOAA
	D: County Level Variables	
SLR_c	The expected mean annual loss computed assuming a 40cm rise in sea level, in percentage of a city's GDP. Cities are mapped to counties, and counties with no expected losses or situated inland are assigned 0.	(Hallegatte et al., 2013)
$\text{GdpPerCapita}_{c,t}$	Current-dollar GDP in county c and year t divided by the Population of county c in year t.	Bureau of Economic Analysis and USDA
$\text{Unemployment}_{c,t}$	The unemployment rate of county c in year t, expressed in percentage.	U.S. Bureau of Labor Statistics
$\text{Population}_{c,t}$	Population of county c in year t.	USDA
Education_c	The college completion rate obtained as the percent of adults with a bachelor's degree or higher averaged for years 2014-2018, for county c.	USDA and ACS 5-year
$\text{Income}_{c,t}$	Per capita income of county c in year t expressed in thousands of dollars .	Bureau of Economic Analysis
$\text{DefaultRate}_{c,t}$	The percentage of mortgages 30–89 days delinquent for county c in year t, expressed in percentage.	CFPB

Table 2: Counties With Sea Level Rise Exposure

This table presents cities and counties ranked by sea level rise (SLR) exposure. The SLR measure estimates expected mean annual losses as a percentage of a city's GDP, assuming a 40 cm rise in the sea level as of 2050 and that cities attempt to adapt to this rise, as computed by (Hallegatte et al., 2013). All counties not included in this table are assigned a SLR of zero.

City	State	Counties	Sea Level Rise Exposure
New Orleans	LA	Orleans	1.479%
Miami	FL	Dade	0.420%
Tampa, St. Petersburg	FL	Hillsborough, Pinellas	0.324%
Virginia Beach	VA	Virginia Beach	0.173%
Boston	MA	Suffolk	0.149%
Baltimore	MD	Baltimore	0.104%
LA, Long Beach, Santa Ana	CA	Los Angeles, Orange	0.097%
New York, Newark	NY	Bronx, Kings, NY, Queens, Richmond, Essex	0.089%
Providence	RI	Providence	0.083%
Philadelphia	PA	Philadelphia	0.044%
San Francisco, Oakland	CA	San Francisco, Alameda	0.042%
Houston	TX	Walker, Montgomery, Liberty, Waller, Austin, Harris, Chambers, Colorado, Wharton, Fort Bend,Galveston, Brazoria, Matagorda	0.038%
Seattle	WA	King	0.023%
Washington D.C.	DC	Washington	0.016%
San Diego	CA	San Diego	0.004%
Portland	OR	Multnomah	0.002%
San Jose	CA	Santa Clara	0.001%

Table 3: Summary Statistics

This table presents the descriptive statistics for the sample of U.S. corporate bonds issued between 2010 and 2018. Panel A presents the descriptive statistics for the entire sample of bonds. Panel B focuses on investment grade bonds (bonds with a rating of BBB- on the Standard & Poor's scale or better, equivalent to 13-22 in numerical terms) while Panel C provides statistics for high yield bonds (credit rating strictly below 13). All bond characteristics are obtained from FISD Mergent. Yield spreads at issue are obtained by taking the difference between the bond's offering yield and a treasury bond with matching maturity. Credit ratings are, by order of priority, obtained from SP, Moody's or Fitch, and transformed to numerical values, ranging from 1 (D) to 22 (AAA). The offering price is the price at issue of the bond, maturity is expressed in number of years, and the amount at issue is log transformed. Issuer characteristics are obtained from Compustat on an annual basis. Size is the log of total assets, ROA the ratio between net income and total assets, leverage the ratio between debt (long term and current) and total assets, MtB the market-to-book ratio, and PPE the amount of property, plants and equipment relative to total assets. Sea level rise (SLR) is the exposure to climate change risk at branch locations. It is weighted by the fraction of sales (SLR_Sales), employees (SLR_Employ) and number of branches (SLR_Branch) of each issuer. NbrCounties is the number of counties in which an issuer has branches and HHI_Sales is a Herfindahl–Hirschman Index computed as the sum of squared county-level sales market-shares. Inland captures the percentage of branches located inland. GDP per Capita and Unemployment reflect economic conditions at corporate headquarters.

Panel A: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
YieldSpread (%)	6,286	2.303	2.771	0.004	1.000	2.533	64.136
OfferingYield (%)	6,286	4.418	2.649	0.511	3.049	5.001	64.250
TreasuryYield (%)	6,286	2.115	0.860	0.078	1.583	2.760	4.690
CreditRating	6,286	14.611	3.176	4	13	17	22
OfferingPrice	6,286	99.783	1.468	25.000	99.733	100.000	109.750
Coupon (%)	6,286	4.393	2.647	0.450	3.000	5.000	64.250
Maturity	6,286	11.109	9.060	0.178	5.040	10.195	100.011
Amount	6,286	11.927	2.476	2.890	10.157	13.528	16.524
Size	6,286	11.007	2.095	4.270	9.352	12.579	14.761
ROA	6,286	0.040	0.061	−1.236	0.008	0.067	0.443
Leverage	6,286	0.371	0.178	0.000	0.245	0.492	1.850
MtB	6,286	1.606	0.878	0.510	1.005	1.857	8.607
PPE	6,286	0.219	0.259	0.000	0.012	0.344	0.968
SLR_Sales (%)	6,286	0.016	0.037	0.000	0.003	0.019	1.434
SLR_Employ (%)	6,286	0.018	0.037	0.000	0.004	0.024	1.422
SLR_Branch (%)	6,286	0.016	0.021	0.000	0.007	0.022	0.740
NbrCounties	6,286	250.611	398.253	1	27	233	2,568
HHI_Sales	6,286	0.189	0.219	0.000	0.032	0.270	1.000
Inland (%)	6,286	66.924	16.400	0.000	57.332	77.966	100.000
GdpPerCapita	6,286	148.672	125.110	20.036	63.743	300.442	437.142
Unemployment (%)	6,286	6.262	2.140	2.000	4.500	7.800	15.500

Panel B: Descriptive Statistics for Investment Grade Bonds

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
YieldSpread (%)	4,952	1.862	2.816	0.004	0.891	1.822	64.136
OfferingYield (%)	4,952	4.008	2.661	0.511	2.865	4.500	64.250
TreasuryYield (%)	4,952	2.146	0.900	0.078	1.608	2.800	4.690
CreditRating	4,952	15.894	2.023	13	14	17	22
OfferingPrice	4,952	99.733	1.573	25.000	99.683	100.000	106.949
Coupon (%)	4,952	3.978	2.659	0.450	2.850	4.500	64.250
Maturity	4,952	12.040	9.857	0.178	5.035	12.036	100.011
Amount	4,952	11.880	2.538	2.890	9.710	13.528	16.524
Size	4,952	11.496	1.919	6.020	9.930	13.632	14.761
ROA	4,952	0.046	0.057	−0.705	0.008	0.074	0.349
Leverage	4,952	0.347	0.162	0.000	0.226	0.487	0.921
MtB	4,952	1.663	0.920	0.690	1.006	1.997	8.607
PPE	4,952	0.191	0.245	0.000	0.010	0.290	0.930
SLR_Sales (%)	4,952	0.015	0.018	0.000	0.004	0.020	0.246
SLR_Employ (%)	4,952	0.018	0.019	0.000	0.006	0.026	0.243
SLR_Branch (%)	4,952	0.017	0.014	0.000	0.008	0.022	0.202
NbrCounties	4,952	291.696	422.541	1	45	400	2,568
HHI_Sales	4,952	0.163	0.199	0.000	0.030	0.215	1.000
Inland (%)	4,952	66.842	15.573	0.000	56.425	77.778	100.000
GdpPerCapita	4,952	167.130	131.384	29.774	69.155	305.668	437.142
Unemployment (%)	4,952	6.202	2.105	2.100	4.500	7.800	15.500

Panel C: Descriptive Statistics for High Yield Bonds

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
YieldSpread (%)	1,334	3.940	1.826	0.017	2.603	4.866	12.848
OfferingYield (%)	1,334	5.939	1.965	1.500	4.644	7.001	13.741
TreasuryYield (%)	1,334	1.999	0.678	0.388	1.524	2.405	3.886
CreditRating	1,334	9.847	1.877	4	8	12	12
OfferingPrice	1,334	99.968	0.961	94.000	100.000	100.000	109.750
Coupon (%)	1,334	5.932	1.940	1.500	4.625	7.125	12.750
Maturity	1,334	7.650	3.311	2.962	5.057	10.006	40.068
Amount	1,334	12.099	2.225	3.526	12.346	13.305	15.262
Size	1,334	9.190	1.676	4.270	7.931	10.321	12.309
ROA	1,334	0.016	0.072	−1.236	0.005	0.043	0.443
Leverage	1,334	0.462	0.203	0.019	0.338	0.535	1.850
MtB	1,334	1.395	0.658	0.510	0.991	1.547	7.294
PPE	1,334	0.324	0.283	0.000	0.091	0.540	0.968
SLR_Sales (%)	1,334	0.017	0.073	0.000	0.0004	0.015	1.434
SLR_Employ (%)	1,334	0.017	0.072	0.000	0.001	0.016	1.422
SLR_Branch (%)	1,334	0.015	0.036	0.000	0.002	0.020	0.740
NbrCounties	1,334	98.096	234.802	1	15	58	2,302
HHI_Sales	1,334	0.287	0.259	0.000	0.068	0.450	1.000
Inland (%)	1,334	67.229	19.161	0.000	60.000	78.571	100.000
GdpPerCapita	1,334	80.154	61.022	20.036	51.134	83.114	437.142
Unemployment (%)	1,334	6.485	2.255	2.000	4.700	7.900	13.800

Table 4: Correlation

This table reports the pairwise correlation of the main variables included in the analysis. Yield spreads at issue are obtained by taking the difference between a bond's offering yield and the yield of a matched treasury bond with similar maturity. Credit ratings are, by other of priority, obtained from SP, Moody's or Fitch, and transformed to numerical values, ranging from 1 (D) from the lowest rating to 22 (AAA). Bond maturity is expressed in number of years, and the amount at issue is log transformed. Size is the log of total assets, ROA the ratio between net income and total assets, leverage the ratio between debt (long term and current) and total assets, MtB the market-to-book ratio, and PPE the amount of property, plants and equipment relative to total assets. Sea level rise (SLR) is the exposure to climate change risk at branch locations. It is weighted by the fraction of sales (SLR_Sales), employees (SLR_Employ) and number of branches (SLR_Branch). NbrCounties is the number of counties in which an issuer has branches and HHI_Sales is a Herfindahl–Hirschman Index computed as the sum of squared county-level sales market-shares. Statistical significance at the 0.01%, 0.1%, 1%, 5% levels is indicated by ****,***, **, and * respectively.

	YieldSpread	CreditRating	Maturity	Amount	Size	ROA	Leverage	MtB	PPE	SLR_Sales	SLR_Employ	SLR_Branch	NbrCounties
YieldSpread													
CreditRating	-0.21****												
Maturity	-0.17****	0.10****											
Amount	-0.25****	-0.10****	0.12****										
Size	-0.02	0.61****	0.03*	-0.49****									
ROA	-0.23****	0.24****	0.12****	0.25****	-0.19****								
Leverage	0.09****	-0.31****	-0.03*	-0.23****	-0.04**	-0.11****							
MtB	-0.20****	0.14****	0.08****	0.34****	-0.36****	0.59****	0.04**						
PPE	0.00	-0.28****	0.09****	0.33****	-0.42****	0.01	0.09****	0.10****					
SLR_Sales	0.02	-0.04**	-0.01	0.03*	-0.02	0.04**	0.00	-0.01	-0.01				
SLR_Employ	0.10****	0.01	-0.03**	-0.05****	0.06****	0.01	-0.02	-0.04**	-0.06****	0.96****			
SLR_Branch	0.08****	0.06****	-0.04**	-0.05****	0.09****	0.00	0.00	-0.05****	-0.13****	0.79****	0.81****		
NbrCounties	-0.15****	0.21****	0.10****	0.11****	0.20****	0.12****	-0.04**	0.10****	0.10****	0.00	-0.02	-0.07****	
HHI_Sales	0.25****	-0.15****	-0.18****	-0.09****	-0.08****	-0.10****	-0.06****	-0.04**	0.00	0.06****	0.10****	0.13****	-0.37****

Table 5: Climate Change Risk and Yield Spreads at Issue

This table presents the results of the ordinary least squares regressions of equation (2), where the bond characteristic of interest is yield spreads. Sea level rise (SLR) is the exposure to climate change risk at branch locations. It is weighted by the fraction of sales (SLR_Sales), employees (SLR_Employ) and number of branches (SLR_Branch). Industry and Year fixed effects are included in all specifications. Standard errors are clustered by issuer.

Dependent Variable:		YieldSpread	
Model:	(1)	(2)	(3)
Variables			
SLR_Sales	1.842**		
	(0.8672)		
SLR_Employ		3.978*	
		(2.372)	
SLR_Branch			5.884*
			(3.072)
Maturity	-0.0059	-0.0056	-0.0057
	(0.0132)	(0.0130)	(0.0131)
Amount	-0.3673	-0.3648	-0.3689
	(0.2393)	(0.2374)	(0.2391)
Size	-0.2315	-0.2281	-0.2243
	(0.1454)	(0.1448)	(0.1433)
ROA	-3.14***	-3.262***	-3.161***
	(0.9117)	(0.9436)	(0.9132)
Leverage	2.606***	2.627***	2.578***
	(0.6610)	(0.6655)	(0.6511)
CreditRating	-0.1331	-0.1331	-0.1371
	(0.0950)	(0.0945)	(0.0934)
MtB	-0.2724***	-0.2700***	-0.2645***
	(0.0859)	(0.0848)	(0.0842)
PPE	-0.5824	-0.5750	-0.5912
	(0.4216)	(0.4282)	(0.4365)
GdpPerCapita	0.0036*	0.0036*	0.0036*
	(0.0021)	(0.0021)	(0.0021)
Unemployment	-0.2361**	-0.2387**	-0.2367**
	(0.1087)	(0.1089)	(0.1085)
Fixed-effects			
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Fit statistics			
Observations	6,286	6,286	6,286
R^2	0.4525	0.45456	0.45375
Within R^2	0.22338	0.2263	0.22515

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Climate Change Risk and Credit Ratings at Issue

This table presents the results of the ordinary least squares regressions of equation (2), where the bond characteristic of interest is credit ratings. Sea level rise (SLR) is the exposure to climate change risk at branch locations. It is weighted by the fraction of sales (SLR_Sales), employees (SLR_Employ) and number of branches (SLR_Branch). Industry and Year fixed effects are included in all specifications. Standard errors are clustered by issuer.

Dependent Variable:		CreditRating	
Model:	(1)	(2)	(3)
Variables			
SLR_Sales	-0.6176		
	(1.073)		
SLR_Employ		-0.3283	
		(1.305)	
SLR_Branch			3.411
			(3.63)
Maturity	0.0046	0.0046	0.0049
	(0.0044)	(0.0044)	(0.0044)
Amount	-0.0163	-0.0167	-0.0179
	(0.0531)	(0.0529)	(0.0523)
Size	1.282***	1.283***	1.288***
	(0.0688)	(0.0687)	(0.0682)
ROA	5.04***	5.019***	4.904***
	(1.563)	(1.563)	(1.549)
Leverage	-5.109***	-5.108***	-5.105***
	(0.4498)	(0.4491)	(0.4469)
MtB	1.069***	1.07***	1.074***
	(0.1196)	(0.1197)	(0.1205)
PPE	-0.1495	-0.1528	-0.1640
	(0.5879)	(0.5872)	(0.5694)
GdpPerCapita	-0.0003	-0.0003	-0.0004
	(0.0011)	(0.0011)	(0.0011)
Unemployment	0.0251	0.0248	0.0228
	(0.0550)	(0.0551)	(0.0548)
Fixed-effects			
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Fit statistics			
Observations	6,286	6,286	6,286
R^2	0.75764	0.75761	0.75806
Within R^2	0.59136	0.5913	0.59206

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Excluding Exclusively Coastal and Inland Bond Issuers

This table presents the results of the ordinary least squares regressions defined in equation (2) where the bond characteristic of interest is yield spreads, after excluding bond issuers with branches located exclusively in coastal counties with no SLR exposure, and inland. SLR is the exposure to climate change risk at branch locations, weighted by the fraction of sales (SLR_Sales), employees (SLR_Employ) and number of branches (SLR_Branch). All specifications include year and industry fixed effects, as well as baseline control variables (Maturity, Amount, Size, ROA, Leverage, CreditRating, MtB, PPE, GdpPerCapita, and Unemployment). Standard errors are clustered by issuer.

Panel A: Excluding Firms with Branches Exclusively Coastal with no SLR Exposure

Dependent Variable:	YieldSpread		
Model:	(1)	(2)	(3)
Variables			
SLR_Sales	1.85**		
	(0.8687)		
SLR_Employ		3.988*	
		(2.376)	
SLR_Branch			5.93*
			(3.088)
Controls	Yes	Yes	Yes
Fixed-effects			
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Fit statistics			
Observations	6,279	6,279	6,279
R^2	0.45272	0.45479	0.45399
Within R^2	0.22336	0.22629	0.22516

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Excluding Firms with Branches Exclusively Inland

Dependent Variable:	YieldSpread		
Model:	(1)	(2)	(3)
Variables			
SLR_Sales	1.94**		
	(0.8711)		
SLR_Employ		4.059*	
		(2.353)	
SLR_Branch			6.129**
			(3.09)
Controls	Yes	Yes	Yes
Fixed-effects			
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Fit statistics			
Observations	6,137	6,137	6,137
R^2	0.44782	0.44995	0.44917
Within R^2	0.2146	0.21764	0.21652

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: Placebo Test

This table reports the results from a placebo test, where SLR risk is assigned to placebo neighboring counties ($NeighborSLR$) or placebo matched counties ($MathedSLR$). Actual counties with SLR exposure are assigned a SLR value of 0. Placebo neighbor counties are the closest neighboring non-coastal counties. $NeighborSLR$ is the resulting SLR exposure, weighted by the fraction of sales, employees and number of branches. Placebo matched counties are obtained using nearest neighbor propensity score matching obtained by estimating a logit regression of the treatment dummy (equal to 1 if a county is exposed to SLR risk and 0 otherwise) with local economic conditions (GDP per capita, unemployment, population, default rates, education, income). $MatchedSLR$ is the resulting SLR exposure, weighted by the fraction of sales, employees and number of branches. Neighbor and matched counties are listed in Appendix table A.3 and average economic conditions are reported in table A.4. The estimates are ordinary least squares regressions of equation (2), where the bond characteristic of interest is yield spreads. All specifications include year and industry fixed effects, as well as baseline control variables (Maturity, Amount, Size, ROA, Leverage, CreditRating, MtB, PPE, GdpPerCapita, and Unemployment). Standard errors are clustered by issuer.

Dependent Variable:	YieldSpread					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
NeighborSLR_Sales	-8.532					
	(6.728)					
NeighborSLR_Employ		-11.19				
		(8.936)				
NeighborSLR_Branch			-10.48			
			(8.494)			
MatchedSLR_Sales				-4.704		
				(3.678)		
MatchedSLR_Employ					-0.3704	
					(2.492)	
MatchedSLR_Branch						-3.685
						(4.922)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	6,286	6,286	6,286	6,286	6,286	6,286
R^2	0.45258	0.45315	0.4523	0.45305	0.45193	0.4522
Within R^2	0.22349	0.2243	0.2231	0.22416	0.22257	0.22296

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Inverse Propensity Weighing

In this table, I present the results from the inverse propensity weighted baseline regression for yield spreads as defined in equation (2). Propensity scores are estimated using a logit regression of the treatment dummy (equal to one if the issuer has above median levels of SLR exposure) with the set of bond characteristics (credit rating, amount issued, issuer size), firm characteristics (ROA, leverage, MtB, PPE) and economic conditions (GDP per capita, unemployment, population, default rates, education, income). First stage results for SLR_Sales are provided in the Appendix (table A.4). SLR is the exposure to climate change risk at branch locations, weighted by the fraction of sales (SLR_Sales), employees (SLR_Employ) and number of branches (SLR_Branch). All specifications include year and industry fixed effects, as well as baseline control variables (Maturity, Amount, Size, ROA, Leverage, CreditRating, MtB, PPE, GdpPerCapita, and Unemployment). Standard errors are clustered by issuer.

Dependent Variable:		YieldSpread	
Model:	(1)	(2)	(3)
Variables			
SLR_Sales	1.309***		
	(0.4658)		
SLR_Employ		3.978*	
		(2.372)	
SLR_Branch			5.884*
			(3.072)
Controls	Yes	Yes	Yes
Fixed-effects			
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Fit statistics			
Observations	6,286	6,286	6,286
R^2	0.3152	0.45456	0.45375
Within R^2	0.31926	0.2263	0.22515

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Spatial Dispersion

In this table, I examine the effects of geographic dispersion proxied by the number of counties in which an issuer has branches. Panel A reports estimates of the baseline regression relating SLR exposure and yields spreads after excluding issuers in the top decile of geographic dispersion, located in more than 802 U.S. counties. Panel B divides the sample into two subsamples, geographically diversified firms (above median number of counties) and geographically concentrated firms (below median). SLR is the exposure to climate change risk at branch locations, weighted by the fraction of sales (SLR_Sales), employees (SLR_Employ) and number of branches (SLR_Branch). All specifications include year and industry fixed effects, as well as baseline control variables (Maturity, Amount, Size, ROA, Leverage, CreditRating, MtB, PPE, GdpPerCapita, and Unemployment). Standard errors are clustered by issuer.

Panel A: Excluding Geographically Diversified Issuers

Dependent Variable:	YieldSpread		
Model:	(1)	(2)	(3)
Variables			
SLR_Sales	1.48*		
	(0.7880)		
SLR_Employ		3.415*	
		(1.961)	
SLR_Branch			4.807*
			(2.584)
Controls	Yes	Yes	Yes
Fixed-effects			
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Fit statistics			
Observations	5,656	5,656	5,656
R^2	0.46738	0.46897	0.46823
Within R^2	0.23648	0.23877	0.23771

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Low vs High Spatial Dispersion

Dependent Variable:	YieldSpread					
Subsample:	Low Spatial Dispersion (below median)			High Spatial Dispersion (above median)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
SLR_Sales	2.135***			-1.755		
	(0.5995)			(1.68)		
SLR_Employ		3.542***			-1.125	
		(1.043)			(2.182)	
SLR_Branch			1.828*			5.395
			(1.065)			(8.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,143	3,143	3,143	3,143	3,143	3,143
R^2	0.59542	0.59688	0.59476	0.66897	0.66873	0.66935
Within R^2	0.33036	0.33278	0.32927	0.4995	0.49913	0.50008

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Alternative Measure of Spatial Dispersion

In this table, I examine the effects of geographic dispersion proxied by an Herfindahl–Hirschman Index computed as an issuer's annual squared sum of county-level sales market-share (HHI_Sales). The sample is divided in into two subsamples, geographically diversified firms (below median HHI_Sales) and geographically concentrated firms (above median HHI_Sales). SLR is the exposure to climate change risk at branch locations, weighted by the fraction of sales (SLR_Sales), employees (SLR_Employ) and number of branches (SLR_Branch). All specifications include year and industry fixed effects, as well as baseline control variables (Maturity, Amount, Size, ROA, Leverage, CreditRating, MtB, PPE, GdpPerCapita, and Unemployment). Standard errors are clustered by issuer.

Dependent Variable:	YieldSpread					
Subsample:	Low Spatial Dispersion (above median)			High Spatial Dispersion (below median)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
SLR_Sales	2.291**			1.745		
	(1.051)			(1.84)		
SLR_Employ		3.478*			0.6527	
		(1.861)			(2.061)	
SLR_Branch			4.427*			0.3563
			(2.455)			(4.075)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,253	3,253	3,253	3,033	3,033	3,033
R^2	0.52048	0.52172	0.52059	0.73079	0.73058	0.73056
Within R^2	0.28105	0.28291	0.28122	0.59517	0.59486	0.59482

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12: Industry Heterogeneity

This table reports the baseline results relating sales-weighted SLR exposure and yields spreads, by industry group. Panel A identifies industries that are know to be vulnerable to climate risk (Agriculture, Food, Communication, Energy, Health Care and Transportation). Panel B reports the baseline results by type of vulnerable industry. SLR is the exposure to climate change risk at branch locations, weighted by the fraction of sales (SLR_Sales). All specifications include year fixed effects and baseline control variables (bond maturity, credit rating, amount issued, issuer size, ROA, leverage, MtB, PPE, GDP per capita and unemployment rate at headquarters). Standard errors are clustered by issuer.

Panel A: Vulnerable vs Non-Vulnerable Industries

Dependent Variable:	YieldSpread	
Model:	(1)	(2)
Industry:	Vulnerable	Non-Vulnerable
Variables		
SLR_Sales	0.8483***	2.737
	(0.2801)	(2.223)
Controls	Yes	Yes
Fixed-effects		
Year	Yes	Yes
Fit statistics		
Observations	1,131	5,155
R^2	0.73596	0.31469
Within R^2	0.71216	0.13872

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Breakdown by Vulnerable Industry Group

Dependent Variable:	YieldSpread				
Model:	(1)	(2)	(3)	(4)	(5)
Industry:	Agriculture and Food	Communication	Energy	Health Care	Transportation
Variables					
SLR_Sales	-7.089	7.131	0.7523***	-6.997	-15.56**
	(5.268)	(11.7)	(0.1820)	(10.76)	(7.521)
Controls	Yes	Yes	Yes	Yes	Yes
Yes					
Fixed-effects					
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	150	367	371	54	189
R^2	0.85172	0.78916	0.7774	0.88498	0.75741
Within R^2	0.83134	0.75825	0.76321	0.84573	0.70525

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13: Climate Change Risk and Investment Horizon

This table reports the baseline regression results for yield spreads as defined in equation (2), by investment horizon. Column (1) presents the results for bonds with maturities below 5 years, column (2) with maturities ranging from 5 to 10 years, column (3) with maturities from 10 to 30 years, and column (4) with maturities longer than 30 years. SLR is the exposure to climate change risk at branch locations, weighted by the fraction of sales (SLR_Sales). All specifications include year fixed effects and baseline control variables (bond maturity, credit rating, amount issued, issuer size, ROA, leverage, MtB, PPE, GDP per capita and unemployment rate at headquarters). Standard errors are clustered by issuer.

Dependent Variable:	YieldSpread			
Model:	(1)	(2)	(3)	(4)
Issue Maturity:	<5 Years	5-10 Years	10-30 Years	>30 Years
Variables				
SLR_Sales	13.28**	0.6769**	-1.023	-0.5454
	(5.69)	(0.2672)	(0.9265)	(2.467)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Fit statistics				
Observations	937	2,281	2,374	694
R^2	0.72457	0.78693	0.65791	0.42712
Within R^2	0.27738	0.66048	0.50132	0.30223

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix

Table A.1: Additional Descriptive Statistics and Sample Construction

This table provides additional statistics about the sample of bonds. Panel A reports the number of bonds issued each year. Panel B presents the maturity distribution for the entire sample of bonds, for investment grade bonds (credit rating above or equal to 13, equivalent to BBB- in Standard & Poor's scale), and for High Yield bonds (credit rating below 13). Panel C provides an overview of the sample construction and filters.

Panel A: Number of bonds Issued each Year

Year	Number of Bonds Issued
2010	774
2011	530
2012	734
2013	711
2014	796
2015	788
2016	704
2017	769
2018	480
Total	6,286

Panel B: Maturity Distribution by Bond Credit Quality

Maturity	All Bonds	Investment Grade Bonds	High Yield Bonds
(0,5]	937	750	187
(5,10]	2281	1475	806
(10,15]	1899	1575	324
(15,20]	134	132	2
(20,25]	212	209	3
(25,30]	129	129	0
(30,35]	631	621	10
(35,40]	3	3	0
(40,45]	28	26	2
(45,50]	6	6	0
(50,55]	12	12	0
(55,60]	0	0	0
(60,100]	12	12	0
Total	6,286	4,952	1,334

Panel C: Sample Construction

	Number of bonds
FISD Mergent	85,771
After merging with Compustat	14,534
After merging with SRAF	13,627
After removing missing key variables	9,616
Keeping only fixed coupon bonds	6,947
After removing negative yield spreads	6,759
After merging with Infogroup	6,286
TOTAL	6,286

Table A.2: Additional Robustness

This table presents the results of the ordinary least squares regressions of equation (2), where the bond characteristic of interest is yield spreads and the explanatory variable, SLR exposure, is either log transformed or transformed into a dummy variable. LogSLR is obtained by taking the natural logarithm of weighted SLR exposure by sales, employees and number of branches. Dummy SLR is obtained by weighing a county-level dummy variable equal to 1 if SLR risk is positive and 0 otherwise, instead of the expected mean annual losses as a percentage of a city's GDP. All specifications include year and industry fixed effects, as well as baseline control variables (Maturity, Amount, Size, ROA, Leverage, CreditRating, MtB, PPE, GdpPerCapita, and Unemployment). Standard errors are clustered by issuer.

Dependent Variable:	YieldSpread					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
LogSLR_Sales	2.644*					
	(1.446)					
LogSLR_Employ		6.557*				
		(3.559)				
LogSLR_Branch			7.455**			
			(3.797)			
DummySLR_Sales				2.416**		
				(0.9803)		
DummySLR_Employ					1.407**	
					(0.7029)	
DummySLR_Branch						2.215**
						(0.9769)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	6,286	6,286	6,286	6,286	6,286	6,286
R^2	0.45254	0.45569	0.45406	0.47448	0.45921	0.46158
Within R^2	0.22344	0.22791	0.22559	0.25456	0.2329	0.23626

Firm standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.3: Matched Counties

This table provides the names, FIPS codes and state abbreviations of the neighbor counties and matched counties used in the placebo test. Neighbor counties are the closest neighboring non-coastal counties, based on distance. Matched counties are matched by propensity scores obtained from a logit regression relating the probability of a county having SLR exposure, and county-level variables (GDP per capita, Population, Unemployment, Education and Income).

County FIPS	County Name	State	Neighbor FIPS	Neighbor Name	Neighbor State	Matched FIPS	Matched Name	Matched State
6001	Alameda County	CA	6077	San Joaquin County	CA	48439	Tarrant County	TX
6037	Los Angeles County	CA	6029	Kern County	CA	17031	Cook County	IL
6059	Orange County	CA	6071	San Bernardino County	CA	9001	Fairfield County	CT
6073	San Diego County	CA	6065	Riverside County	CA	32003	Clark County	NV
6075	San Francisco County	CA	6113	Yolo County	CA	6081	San Mateo County	CA
6085	Santa Clara County	CA	6099	Stanislaus County	CA	12099	Palm Beach County	FL
11001	District of Columbia	DC	24031	Montgomery County	MD	39049	Franklin County	OH
12057	Hillsborough County	FL	12105	Polk County	FL	42091	Montgomery County	PA
12086	Miami-Dade County	FL	12051	Hendry County	FL	36119	Westchester County	NY
12103	Pinellas County	FL	12049	Hardee County	FL	48453	Travis County	TX
22071	Orleans Parish	LA	28109	Pearl River County	MS	48215	Hidalgo County	TX
24005	Baltimore County	MD	24013	Carroll County	MD	48329	Midland County	TX
25025	Suffolk County	MA	25027	Worcester County	MA	42003	Allegheny County	PA
34013	Essex County	NJ	34027	Morris County	NJ	9003	Hartford County	CT
36005	Bronx County	NY	34037	Sussex County	NJ	40143	Tulsa County	OK
36047	Kings County	NY	34019	Hunterdon County	NJ	26163	Wayne County	MI
36061	New York County	NY	34031	Passaic County	NJ	48113	Dallas County	TX
36081	Queens County	NY	34041	Warren County	NJ	6071	San Bernardino County	CA
36085	Richmond County	NY	34021	Mercer County	NJ	8041	El Paso County	CO
41051	Multnomah County	OR	53011	Clark County	WA	34029	Ocean County	NJ
42101	Philadelphia County	PA	42091	Montgomery County	PA	36103	Suffolk County	NY
44007	Providence County	RI	9015	Windham County	CT	48085	Collin County	TX
48015	Austin County	TX	48477	Washington County	TX	17055	Franklin County	IL
48039	Brazoria County	TX	48041	Brazos County	TX	53077	Yakima County	WA
48071	Chambers County	TX	48199	Hardin County	TX	13285	Troup County	GA
48089	Colorado County	TX	48285	Lavaca County	TX	19197	Wright County	IA
48157	Fort Bend County	TX	48051	Burleson County	TX	6095	Solano County	CA
48167	Galveston County	TX	48241	Jasper County	TX	42079	Luzerne County	PA
48201	Harris County	TX	48407	San Jacinto County	TX	4013	Maricopa County	AZ
48291	Liberty County	TX	48457	Tyler County	TX	18067	Howard County	IN
48321	Matagorda County	TX	48123	DeWitt County	TX	18083	Knox County	IN
48339	Montgomery County	TX	48373	Polk County	TX	42045	Delaware County	PA
48471	Walker County	TX	48313	Madison County	TX	55053	Jackson County	WI
48473	Waller County	TX	48185	Grimes County	TX	55115	Shawano County	WI
48481	Wharton County	TX	48149	Fayette County	TX	13129	Gordon County	GA
51810	Virginia Beach city	VA	51183	Sussex County	VA	33011	Hillsborough County	NH
53033	King County	WA	53037	Kittitas County	WA	36059	Nassau County	NY

Table A.4: Economic Conditions of Neighbor and Matched Counties

This table presents average economic conditions from 2010-2018 for SLR counties, as defined in table 2, neighbor counties and matched counties. Neighbor counties are the closest neighboring non-coastal counties, based on distance. Matched counties are matched by propensity scores obtained from a logit regression relating the probability of a county having SLR exposure, and county-level variables (GDP per capita, Population, Unemployment, Education and Income).

Counties	GDP Per Capita	Population	Unemployment (%)	Education (%)	Income (%)
SLR Counties	70.50	1340398.98	6.58	33.99	53717.66
Neighbor Counties	48.10	358370.71	7.11	25.32	44063.07
Matched Counties	58.08	1028591.64	6.49	31.03	52752.13

Table A.5: Estimating the Probability of High SLR Exposure

This table reports the first stage logit used to obtain propensity score for the inverse propensity weighting analysis described in table 9. The logit regression relates the probability of having above-median levels of SLR exposure (HighSLR_Sales) with bond characteristics (Maturity, Amount), issuer characteristics (Size, ROA, Leverage, Credit Rating, MtB, PPE) , and weighted county-level control variables (GDP per capita, Population, Default Rates, Unemployment, Education and Income).

	Dependent variable:
	HighSLR_Sales
Maturity	0.014***
	(0.004)
Amount	0.143***
	(0.023)
Size	0.232***
	(0.038)
ROA	4.594***
	(0.886)
Leverage	0.295
	(0.230)
CreditRating	−0.027
	(0.018)
MtB	0.100*
	(0.059)
PPE	−0.337*
	(0.177)
GdpPerCapita_Sales	0.012***
	(0.003)
Unemployment_Sales	0.164***
	(0.025)
Population_Sales	0.00000***
	(0.00000)
DefaultRate_Sales	0.035***
	(0.009)
Education_Sales	−0.060***
	(0.009)
Income_Sales	0.00005***
	(0.00001)
Constant	−9.894***
	(0.564)
Observations	6,286
Log Likelihood	−2,920.215
Akaike Inf. Crit.	5,870.431
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.6: Geographic Branch Location By Industry

This table reports geographic information and SLR exposure by vulnerable industry group. Vulnerable industries are those that are known to be vulnerable to physical climate risk (Agriculture, Food,Communication, Energy, Health Care and Transportation). NbrCounties is the number of counties in which an issuer has branches. HHI_Sales is a Herfindahl–Hirschman Index computed as the sum of squared county-level sales market-shares. Inland captures the percentage of branches located inland.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Vulnerable Industries							
NbrCounties	1,131	349.502	433.067	1	27	639.5	1,422
HHI_Sales	1,131	0.173	0.223	0.000	0.025	0.227	1.000
Inland (%)	1,131	75.836	16.633	0.000	69.783	85.714	100.000
SLR_Sales (%)	1,131	0.017	0.075	0.000	0.001	0.019	1.434
Agriculture and Food							
NbrCounties	150	83.567	72.145	3	31	118	405
HHI_Sales (%)	150	0.168	0.162	0.018	0.070	0.216	0.745
Inland	150	75.958	13.904	27.500	68.254	86.854	100.000
SLR_Sales (%)	150	0.007	0.015	0.000	0.0002	0.005	0.071
Communication							
NbrCounties	367	699.253	459.063	1	320	1,129	1,422
HHI_Sales (%)	367	0.084	0.143	0.006	0.009	0.056	1.000
Inland	367	72.450	13.546	0.000	69.863	78.746	100.000
SLR_Sales (%)	367	0.022	0.021	0.000	0.012	0.020	0.189
Energy							
NbrCounties	371	177.911	331.913	1	6	87.5	1,345
HHI_Sales	371	0.300	0.280	0.000	0.082	0.462	1.000
Inland (%)	371	81.016	20.583	0	77.9	94.7	100
SLR_Sales (%)	371	0.018	0.128	0	0	0.01	1
Health Care							
NbrCounties	54	308.148	254.706	28	48	521	812
HHI_Sales	54	0.059	0.086	0.007	0.029	0.059	0.625
Inland (%)	54	72.011	9.047	55.882	67.540	74.954	93.750
SLR_Sales (%)	54	0.019	0.016	0.000	0.005	0.031	0.051
Transportation							
NbrCounties	189	230.058	331.085	2	77	206	1,293
HHI_Sales	189	0.134	0.173	0.007	0.037	0.158	0.962
Inland (%)	189	73.236	14.468	10.000	62.500	85.714	93.103
SLR_Sales (%)	189	0.013	0.016	0.000	0.002	0.013	0.075