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Climate Risk and Capital Structure

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May 2023

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Abstract

We use firm-level data that measure forward-looking physical climate risk to examine the impact of climate risk on capital structure. We find that greater physical climate risk leads to lower leverage in the post-2015 period, i.e., after the Paris Agreement and the first step of standardization of disclosure of climate risk information. Our results hold after controlling for firm characteristics known to determine leverage, including credit ratings. Our evidence shows that the reduction in leverage related to climate risk is shared between a demand effect (the firm's optimal leverage decreases) and a supply effect (bankers and bondholders increase spreads when lending to firms with the greatest risk). Our results are consistent with the hypothesis that physical climate risk affects leverage via larger expected distress costs and higher operating costs.

Keywords: Physical climate risk, Climate change exposure, Paris Agreement, Capital structure, Leverage, Credit rating, ESG

JEL Classifications: G18, G2, G32, Q54

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Climate Risk and Capital Structure*

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1. Introduction

As the Intergovernmental Panel on Climate Change (IPCC) assessment reports highlight, climate change is accelerating, with a documented increase in average temperature[1] and dramatic effects of sea-level rise and weather-related natural catastrophes, such as droughts, storms, heatwaves, floods, and wildfires. Several recent papers emphasize that climate risk affects the pricing of stocks, bonds, and real estate (Bernstein et al. 2019, Painter 2020, and Seltzer et al. 2020), and a majority of institutional investors believe that climate risk is an important concern (Krueger et al. 2020). Investors face potential losses from climate change consequences in terms of physical and transition risks. Physical climate risks may lead to a reassessment of the value of a large range of firms' assets (plants, property, and equipment) and to increased operating costs, such as relocation costs and insurance costs, resulting in lower profits and reduced repayment capacity. The transition risks stem from increased financial and nonfinancial regulations, carbon taxes, changing stakeholder preferences, and climate-related technological disruptions. Our analysis focuses on physical risks. Several articles have analyzed the impact of past major climate events on companies' value and financial decisions (see, for example, Hong et al. 2019, and Brown et al. 2021). However, quantifying the future physical risks that will threaten the company requires relying on scientists' projections and assessment of the company's exposure to these risks.

In this paper, we use forward-looking firm-level measures to examine whether the physical climate risks faced by a firm have an impact on its capital structure. Under a Modigliani and Miller (1958) framework, climate risk should play no role. However, in the presence of market frictions, climate risk is likely to alter the tradeoff between the benefits and costs of debt. We hypothesize that physical climate risk may affect financial leverage via two possible channels: larger expected distress

[1] The IPCC Assessment Report 6, Working Group 1 report (2021) points out that global surface temperature was 1.09°C higher in 2011–2020 than 1850–1900. The estimated increase in temperature since the previous report in 2013 is principally due to further warming since 2003–2012.

costs and higher operating costs.[2] We find strong support for the conclusion that greater climate risk leads to lower leverage in the post-2015 period, i.e., after the Paris Agreement (COP21), a historic global climate deal to limit warming to 2°C by 2100 (and preferably 1.5°C), which was signed by 195 countries in December 2015 and supported by a high degree of commitment from large firms, institutional investors and central banks. The Paris Agreement raised awareness of the extent of climate risks among all stakeholders, leading to a consensus on the need to measure and disclose the long-term risks associated with climate change borne by companies, financial institutions, and insurers. In 2015, the Financial Stability Board (FSB) established the Task Force on Climate-related Financial Disclosures (TCFD), a major step on this path. Regarding physical climate risks, the Task Force recommends that organizations describe the potential financial impacts of, in particular, damage to assets, supply chain interruptions, and increased insurance premiums. The TCFD framework has since become a global standard for climate risk disclosure. Section A in the internet Appendix discusses why the Paris Agreement can be considered a breakthrough step regarding climate risk.

Measuring firm-level exposure to future physical climate risk is challenging. In this paper, we use different metrics of physical climate risk at the firm level. We first rely on the “Climate Risk Impact Screening” (CRIS) methodology developed by a French firm, Carbone 4, with support from several institutional investors and public agencies. The CRIS risk rating is a forward-looking measure that captures the increase in intensity or frequency of climate-related hazards due to climate change at two time horizons, 2050 and 2100. For each firm in the MSCI World Index, climate risk grades are quantified based on climate projections from IPCC models, the geographical division of activities, country-specific vulnerabilities, and industry-specific vulnerabilities.

As a second measure of climate risk, we use alternative data provided by Four Twenty Seven, a provider of data related to physical climate and environmental risks that has been part of Moody’s ESG solutions since July 2019.[3] Four Twenty Seven’s models assess projected exposure to climate hazards

[2] Although some firms will benefit from increased climate risk, for example, those specialized in providing services for adjusting to this risk, most will see negative effects on their earnings. In a study of the effects of climate change and weather effects on earnings for the firms in the S&P500 index, more than 90% of the mentions were negative (S&P Global (2018)).

[3] Moody’s ESG Solutions, a unit of Moody’s Corporation, operates independently of Moody’s Investors Service, the credit rating agency.

at the facility level aggregated at the firm level. They also assess a firm's dependence on natural resources threatened by climate change. Four Twenty Seven provides a composite climate risk score for each firm.

The methods used by these two data providers to quantify physical climate risk are model-based and rely on different scientific databases, granularities, scenarios, and weightings, although their projections are consistent with each other (see details in Appendix B). Climate data providers are subject to various criticisms concerning their lack of transparent scientific validation and proprietary, black-box technology (Keenan, 2019). We have had access to detailed methodological guides describing the scientific choices and the procedures used to construct the indicators and in-depth discussions with members of the teams, including climate scientists. We are thus confident in the reliability of the providers' approach, even if we recognize the complexity of raw climate data and their processing.

To complement these data, we also use as a robustness test an alternative measure relying on a language-based methodology, the Sautner et al. (2022) physical climate risk metric that builds on transcripts of earnings conference calls to capture firms' exposure to climate risk. In contrast to our main metrics, which measure the fundamental exposure to future physical climate risks, the Sautner et al. (2022) metric captures the attention of analysts and other market participants to climate risks by estimating the share of the conversation in a transcript devoted to that topic. The authors argue that earnings calls are largely forward-looking compared to metrics relying on firms' annual reports.

We begin our empirical analysis by estimating the relationship between a firm's leverage ratio and our measures of climate risk. Specifically, we regress the observed debt ratios of the firms that belong to the MSCI World Index over the period 2010-2019 on climate risk measures for each firm in addition to several fixed effects and other control variables. We find that an increased physical climate risk reduces firms' leverage in the post-2015 period, i.e., after the Paris Agreement and the increased climate risk disclosure requirements. Our results are both statistically and economically significant. We find that after 2015, a one standard deviation increase in climate risk generates decreases in book leverage and market leverage ranging from 4.02% to 6.96%, depending on the considered models. The patterns that we observe in our baseline tests remain after various robustness checks that involve changes in empirical specifications, variable construction methods, sampling restrictions, and matching procedures that ensure that firms with high and low climate risk have similar characteristics. Furthermore, by using the 2015 Paris Agreement as a shock to the awareness of firms, bankers and investors of climate risks, we also conduct a difference-in-differences approach to compare the leverage of high climate risk firms versus low climate risk firms before and after the Paris Agreement. Our findings remain unchanged.

Climate risk could also be a component of the overall corporate credit risk; therefore, credit rating agencies (CRAs) should include it in their risk assessment, with credit ratings also reflecting climate risk. Rating agencies are increasingly aware of the need to incorporate the risks and opportunities associated with environmental and climate factors into their corporate credit ratings.[4] However, our results suggest that credit ratings do not reflect all the information related to physical climate risk. In all our tests, we control for credit ratings and find that the physical climate risk grades provide additional information that is not already embedded in credit ratings. We also find that our measures of climate risk do not impact credit ratings when controlling for the usual determinants of credit ratings. Recently, major CRAs have acquired extrafinancial rating agencies, acknowledging the need to strengthen their expertise in climate risk rating, which could result in better recognition of climate risk in the future.[5]

Our tests include several variables to control for other characteristics (size, tangible assets, profitability) that might affect leverage. However, if firms have a discontinuity in characteristics around the 2015 Paris Agreement, these characteristics may be driving our results that leverage decreases for high climate risk firms after 2015. For example, oil prices fell by more than 50% between 2014 and 2016. The strong decrease in oil prices may reduce the debt capacity of firms highly exposed to variations in oil prices. If climate risk is also high for these firms, oil prices could be an alternative explanation for our results. To account for firms' differentiated exposure to oil price changes, we include oil betas, calculated similarly to Ilhan et al. (2021), in all our regressions. We also include an interaction

[4] See, for example, this report from S&P Global Ratings.

[5] For example, S&P acquired Trucost (2016), and Robecom SAM (2019). In addition to Four Twenty Seven, Moody's acquired Vigeo-Eiris (2019). An alternative explanation for our results could be that the horizon at which physical climate risk might materialize is beyond that used by rating agencies given the maturity of corporate debt. See this article on the CRA's time horizon written by an industry player. However, if this were the case, credit rating agencies would not seek to strengthen their climate risk expertise.

term oil beta * post-2015 to account for the specific oil price pattern around the 2015 Paris Agreement, without altering our findings, which also remain similar when we exclude oil and gas industries. Furthermore, we conduct sensitivity tests for other firms' characteristics, all of which support our conclusions that physical climate risk is driving our results.

Although Bolton and Kacperczyk (2022) underline that transition risk does not appear to be significantly related to different exposures to physical risk, one might be concerned that there is a link between physical risk and transition risk and that our results partly reflect the effect of transition risk. We find that our results remain similar when controlling for transition risk, measured by Sautner et al. (2022) regulatory risk exposure, and its interaction with the dummy post-2015, which confirms that physical risk has an effect on leverage, independent of transition risk.

In the traditional empirical capital structure literature, debt supply frictions are not observed, and the firms' characteristics are the main determinants of leverage. In this framework, the observed reduction in leverage would result entirely from firms becoming aware of their climate risks and lowering their leverage. To adjust their leverage, in addition to lowering their demand for debt, high climate risk firms can increase shareholders' equity. We find that, after 2015, high climate risk firms increase their net equity offerings, suggesting that at least a fraction of the reduction in leverage results from a demand effect. Another way to examine the demand side is to review firms' ESG performance. As Engle et al. (2020) underline, ESG performance may act as a hedge against physical and regulatory risks. Our results related to the impact of climate risk on leverage remain unchanged after considering ESG scores, which suggests that physical climate risk is an additional risk besides the environmental issues that nonfinancial rating agencies usually rate. Furthermore, we find that the reduction in leverage is mainly observed for firms with low ESG performance, suggesting that high ESG firms are likely to take proactive actions, for example, implementing appropriate risk management tools, to handle their climate risk rather than decrease their leverage.

On the supply side, bondholders and bankers may be willing to reduce their exposure to climate risks by limiting the amount of debt that they lend to high climate risk firms or by increasing the cost of debt for these firms. To test whether a supply effect occurs, we use loan-level data to examine interest rates charged on bank loans and bonds issues. We find that greater climate risk implies higher spreads on both bank loans and bond issues in the post-2015 period.

Overall, our findings suggest that the reduction in leverage related to climate risk is shared between a demand effect, whereby firms lower their demand for debt or issue more equity, and a supply effect, whereby bankers and bondholders increase the interest rate that they charge to high climate risk firms.

Our paper contributes to several lines of research. First, this research is related to the literature on physical climate risk and its impacts on firms and investors. The macroeconomic literature provides a great deal of evidence of global warming and extreme natural events that affect agricultural output, industrial output, energy demand, labor productivity, health, conflict, political stability and economic growth (see Dell et al. 2014, and Jones and Olken 2010). Evidence on a microeconomic level gives rise to a recently growing body of literature. For example, using country-level climate risk indicators, Huang et al. (2018) find that firms in high climate risk countries hold more cash, have less short-term debt and more long-term debt, and are less likely to pay cash dividends. The drawback of country-level measures is that they potentially capture other country characteristics, such as the efficiency of its financial institutions and markets, which may directly affect outcomes. Barrot and Sauvagnat (2016) examine the impact of natural disasters on sales growth and find that disasters negatively affect both the sales growth of directly exposed firms and their largest customers. Pankratz and Schiller (2021) find that firms adapt their supply chain networks when weather shocks at the locations of their suppliers become more frequent, which can impose a substantial cost on their suppliers. Bansal et al. (2016), Addoum et al. (2019), Hugon and Law (2019), and Pankratz et al. (2019) observe that abnormal temperature negatively impacts firms' earnings and equity valuations, and Brown et al. (2021) examine the effects of climatic events on firms' drawing of bank credit lines. Bernstein et al. (2019) find that coastal properties exposed to projected sea-level rise (SLR) sell at an approximately 7% discount relative to otherwise similar properties. This SLR exposure discount is primarily driven by properties unlikely to be inundated for over half a century, which suggests that this discount is due to investors pricing long-horizon SLR costs. This result emphasizes how climate risk discounts asset values and potentially reduces their pledgeability, which, in turn, may be part of the explanation of the leverage reduction that we document in our study.

Second, our research also contributes to the literature on the impact of climate risk on credit risks. Painter (2020) examines municipal bonds and finds that counties more likely to be affected by sea level rise pay more in underwriting fees and initial yields. Correa et al. (2021) estimate reactions in loan spreads for at-risk corporate borrowers who are not directly affected by natural disasters. Banks charge approximately 8 basis points higher rates for these indirectly affected borrowers.[6] Furthermore, Faiella and Natoli, 2019 find that flood risks decrease the amount of loans granted to corporations. Our results not only confirm these supply-side effects for physical climate risks but also underline that they occur mainly after 2015. Several other articles also find post-2015 effects for transition risks. For example, Seltzer et al. (2020) provide evidence of a causal relationship between climate regulatory risks and bond yield spreads after the 2015 Paris Agreement, and Bolton and Kacperczyk (2022) find a significant increase in the carbon premium after the Paris Agreement, especially for firms belonging to G20 countries. Our paper underlines that the Paris Agreement has also been important in reshaping companies' and investors' beliefs about physical climate risk. Overall, there is currently a strong set of results that emphasize the tangible effects of the rising awareness of bankers and institutional investors regarding climate risks, whether transition risks or physical risks, in the post-2015 period.

Third, our paper is also related to the literature that examines the impact of operating costs on firms' financial leverage. Physical climate risks may increase operating costs (climate resilience expenses, costs related to operational disruptions, supply chain changes, insurance premiums), which could lead to a substitution effect between operating and financial leverage. Several authors examine various types of operating costs and risks and find a negative relationship between operating leverage and financial leverage (Petersen, 1994, Reinartz and Schmid, 2016, Chen et al., 2019, Kahl et al., 2019). In our paper, we rely on forward-looking climate risk measures to proxy for increased operating costs and find that after 2015, the risk related to climate change, even if not yet materialized, leads to a reduction in the leverage of the world's largest firms. Our results also highlight that more ESG-oriented

[6] Several papers find that transition climate risks also increase bond spreads (Seltzer et al. 2020, Huynh and Xia 2021) as well as bank spreads (Delis et al. 2019, Anginer et al. 2020).

firms are better able to manage their operational risk and offset the negative impact of physical climate risks on their capital structure. These findings are in line with Sharfman and Fernando (2008), who find that improved environmental risk management allows for more leverage. They are also consistent with Lins et al. (2017), who find that during the 2008-2009 financial crisis, high ESG firms were able to raise more debt, and Amiraslani et al. (2022), who show that these firms benefited from lower spreads, better credit ratings, and longer maturities. Finally, our results also echo Huynh and Xia's (2022) findings that firms with strong environmental profiles experience lower selling pressure when exposed to natural disasters. These firms benefit from investing in corporate environmental policies, which pay off when physical climate change risk is materialized.

The rest of the paper is structured as follows. In section 2, we present our hypotheses. In section 3, we present our climate risk measures and our dataset. We analyze our empirical results in section 4, and section 5 concludes.

2. Hypothesis development: the effect of physical climate risk on leverage

The three prominent theories of capital structure, static tradeoff theory (Bradley et al. 1984), pecking order (Myers and Majluf 1984), and market timing (Baker and Wurgler 2002), all involve tradeoffs between the costs and benefits of debt financing but differ in their assessment of which market frictions are the most relevant. Overall, although the results vary over time and depend on the type of sample selected and the methodology used, the empirical evidence suggests that firms borrow more when they are subject to lower debt issuance costs, higher corporate taxes, lower bankruptcy costs, a higher liquidation value of assets and lower operating costs and earnings volatility. To assess the impact of climate risk on corporate leverage, we focus on two variables: operating costs and bankruptcy costs.

2.1. Climate risks and operating costs

Firms exposed to physical climate risks will incur climate resilience expenses due to two major factors: first, costs related to operational disruptions, production adjustments, and supply chain changes, and second, increased insurance premiums. Manufacturing operations are increasingly global, complex, and geographically concentrated. For example, Thailand floods in 2011 caused a 37% (55%) loss of operating profit for Toyota (Honda) due to the lack of parts from suppliers whose plants were flooded, Thailand being one of the production hubs for Japanese automakers (Haraguchi and Lall, 2015). In 2017, Hurricane Maria made landfall on Puerto Rico, where 10% of US pharmaceutical product manufacturing is based, and led to critical shortages throughout the US.[7] In a survey on supply chain resilience[8], respondents cite adverse weather as one of the top three causes of supply chain disruptions. In addition, anecdotal evidence shows that some companies prefer to take the risk of increasing operating costs rather than relocating their production facilities.[9]

The increase in insurance premiums is another major factor in the rise in operating costs. Two key variables affect the insurability of climate risk events. First, natural disasters are hardly diversifiable, as they simultaneously hit thousands of insurance policies for property, cars, and business interruptions. This systematic nature of climate risks will require additional capital and safety margins in premium calculations (Kunreuther and Michel-Kerjan, 2007, and Charpentier, 2008). Second, it is becoming less and less relevant to rely only on past events to estimate future climate risk. However, if insurers update their models and add a large margin to the premium to allow for uncertainty, the likelihood of an agreement between insurers and policyholders on the perception of risk, and thus on the premiums to be paid, decreases. As a result, a significant number of insurers exit this market (Born and Viscusi 2006). In addition, as a growing number of insurers are considering not renewing insurance contracts for clients

[7] See DHS report (2018).
[8] BCI, Supply chain resilience report (2019).
[9] See US department of commerce report (2022) "Assessment of the critical supply chains supporting the US ICT industry", p74-75. Before 2011, Thailand produced approximately 45% of the world's hard disk drive (HDD) components. After the 2011 floods, while experts called for increased geographic diversity, HDD production further consolidated in Thailand, increasing the potential impact of future natural disasters.

or sectors most at risk, increased uncertainty and reduced competition will inevitably lead to higher insurance premiums in the future.[10]

The existence since 2015, thanks to the TCFD, of standards for the disclosure of the companies' climate risks could have made it possible for companies and insurers to more easily converge in their assessments of the actual increasing risk and facilitate the insurability of risks at a higher premium. Similarly, disclosure requirements have probably also led companies to an increased awareness of the risks of their entire supply chain and a more accurate assessment of the consequences of these risks. Following the prior literature (Reinartz and Schmid 2016, Chen et al. 2019), we hypothesize a substitution effect between operating and financial leverage.

2.2. Climate risks and bankruptcy costs

Second, climate risk can impact the costs associated with a possible failure. The value of a firm's assets may be reduced if they are located in areas subject to significant climatic risks. The impairment may be related to direct asset destruction by an extreme climatic event or to a reduction of asset value due to their exposure to future climate risks (for example, seashore property exposed to a sea-level rise). In addition, a loss in the assets' market value may also result from the inability to sell these assets to an acquirer due to increased climate risks.[11] Insurance companies can partly mitigate the first type of cost (asset destruction by extreme events) but do not cover the second type.

The traditional hypothesis in the empirical capital structure literature is that the observed level of debt equals the firm's demand level, which means that there is no supply friction. Firm characteristics are then the main determinants of leverage. Therefore, our first hypothesis is that firms with greater climate risk exposure will reassess their operating costs and distress costs, which should lead them to

[10] Examples of current increased insurance premiums: TWIA, the insurer of last resort for wind and hail in counties along the Texas coast, more than doubled insurance premiums since 2000 and states its commercial rates are still inadequate by 50 percent. See here. In the ten Californian counties with highest fire risk exposure, nonrenewed homeowners insurance policies increased by 203% from 2018 to 2019. See here, p.7 and here. For further analysis of wildfires insurance, see Hazra and Gallagher (2022). For a study of the consequences of droughts on the insurance coverage for commercial enterprises, see Kornfeld (2019).

[11] There are also several papers on stranded assets, i.e., assets at risk of becoming obsolete, especially in the oil and electricity industries (see for example Atanasova and Schwartz 2020 and Hickey et al. 2021). However, these impairments are mainly the results of regulatory risks (for example regulations on the reduction of carbon emissions) rather than physical climate risks.

reduce their leverage compared to firms with low exposure to climate risk. To adjust their leverage, high climate risk firms may decrease their demand for debt or issue new shares.

2.3. Climate risk and leverage: is there a supply effect?

Supply-side factors are likely to be important in explaining capital structure (Faulkender and Petersen 2006). There may be climate effects related to the debt supply if bankers and bondholders become increasingly aware of climate risk and subject firms to more stringent regulations and disclosure requirements. The climate risk effects can occur directly through a quantity channel if lenders are willing to lend less to firms exposed to higher climate risk or indirectly through a price channel if lenders are increasing the cost of debt for high climate risk firms. To verify this last effect, we conduct empirical tests by using loan-level data, specifically bank loans on the one hand and bond issues on the other hand. Therefore, our second hypothesis is that climate risk should increase the cost of debt.

To the extent that the many recent climate change initiatives and disclosure requirements have increased the attention of firms, investors, and central banks to climate risk, we assume that the effects of climate risks on capital structure will mainly materialize in the period after 2015.

3. Data

3.1. Physical climate risk measures

The assessment of climate risk at the firm level depends on both geographical factors and vulnerability factors specific to the firm's activity. In this paper, we use two climate risk measures, described in detail in Appendix B. The first is the CRIS methodology, which was developed by the French firm Carbone 4 in cooperation with several financial institutions.[12] Their approach is based on models and data from the Coupled Model Intercomparison Project (CMIP), (see Taylor et al. 2012). The

[12] More information is available here.

CRIS measures aim at assessing the climate-related physical risks that face firms and their business units in the future by breaking down the firm's activity into geographical and industrial segments and by assessing the future climate risk for each country-industry pair. Each climate risk rating is a function of location-specific climate hazards and sector-specific vulnerabilities. The geographical division of activities is based on sales, tangible assets, or a combination of both, depending on the low, high or medium capital intensity of the sector to which the firm belongs. At its broadest level, climate risk is measured through an index that aggregates 7 hazards: heatwaves, rainfall extremes, drought, storms, increases in average temperature, changes in rainfall patterns and sea-level rise.

The CRIS measures are split into two-time horizons (2050 and 2100) and three intensity cases (low, medium, high). In this paper, for the sake of clarity, we use a unique CRIS rating that corresponds to the 2050 horizon and medium intensity risk. This horizon seems distant, as the majority of bond issues have a maturity of less than 30 years, but the reader should keep in mind that climate risk will gradually materialize over the coming years. As Krueger et al. (2020) show in their survey on climate risk, most institutional investors believe that climate risks will materialize within the next few years. The CRIS ratings cover the sphere of the MSCI World Index for 2016.

The second measure of climate risk that we use is provided by Four Twenty Seven.[13] Each firm is scored on three components of physical climate risk: operations risk, supply chain risk, and market risk, with a time horizon of 2030 to 2040. A firm's operations risk is based on its facility-level exposure to hurricanes and typhoons, sea-level rise, floods, extreme heat, and water stress. The supply chain risk is evaluated with two indicators, the country of origin indicator (a measure of climate risk in countries that export commodities that a company depends on for the production and delivery of products and services) and the resource demand indicator (a measure of the industry-level dependence on climate-sensitive resources such as water, land, and energy across the supply chain). Market risk is based on countries of sales and weather sensitivity for market risk.

As climate risk scores are determined based on a 2050 horizon (CRIS) or 2030-2040 (Four Twenty Seven), we assume that this risk remains stable over the period studied (2010-2019) and that the firm's

[13] See here for more information.

activities and locations do not undergo major changes over the period, which is the hypothesis adopted by the two rating companies.[14]

After excluding financial firms and observations with missing data (see below), we are left with 1,212 firms. In Table 1, Panel A presents the descriptive statistics for our climate risk ratings. The average overall CRIS rating is 35.161 (median = 36.994, standard deviation 10.833). The number of observations available for the Four Twenty Seven scores is slightly smaller than that for the CRIS scores, as all MSCI firms are not yet graded. The average overall Four Twenty Seven rating is 42.828 (median = 43.510, standard deviation 13.225).

3.2. Credit ratings

Credit ratings at the issuer level are obtained from Thomson Reuters. This variable is based on the S&P Long-term Issuer Rating when available. If this rating is not available, we rely on Moody's Long-term Issuer Rating, and we rely on Fitch's Long-term Issuer Default Rating if both previous measures are missing. Similar to Baghai et al. (2014), we linearize these ratings from 1 to 20. Investment-grade ratings are coded between 11 and 20, whereas high-yield ratings are coded between 1 and 10. Missing ratings are coded 0.

Of our firm-year observations, 67% are rated and therefore have potential access to public debt markets, which reflects the fact that the sample comprises the world's largest listed firms that belong to the MSCI World Index. The average credit rating is 12.28 (median 12), which corresponds to an S&P grade of BBB.

3.3. Financial and accounting data

The financial and accounting data are from Compustat North America and Compustat Global. We first matched the firms covered by the CRIS grades with the data available in Compustat for fiscal

[14] One question that may arise is how these measures of future climate risk relate to historical climate risk. The Four Twenty Seven score explicitly considers historical risk in assessing future operational risk. The CRIS score assesses the increase in risk over the time horizon under consideration relative to historical risk. Although both measures contain more information than a purely historical measure, we acknowledge that they are not unrelated to the historical risk.

years 2010 to 2017, which yields 11,836 firm-year observations. By relying on 2-digit SIC codes, we excluded SIC codes 60 to 69, as financial firms are subject to special regulations concerning their capital structure. We excluded the observations with missing values of operating expenses and the observations for which we were unable to compute Tobin's Q. Therefore, we were left with 9,138 firm-year observations that cover 1,212 firms. These figures are sound, as, on the one hand, 1,604 firms are covered by CRIS, and on the other hand, the MSCI World Index covers approximately 1,600 firms, with 16.33% of them belonging to the financial sector.[15] We extended our database to 2019, when the data became available. In total, our database covers 11,367 firm-year observations for 1,212 firms (see Appendix A for variable definitions). All the variables computed from Compustat are winsorized at the 1% level to prevent the effect of potential outliers. Country fixed effects are based on headquarters locations, and industry fixed effects are based on the two-digit SIC codes.

In Table 1, Panel B, the means (medians) of various firm characteristics are reported for the full sample and are then disaggregated between low climate risk (below the 40th percentile) and high climate risk (above the 60th percentile) firms. The average long-term book leverage is 21.8%. High climate risk firms (with an average CRIS rating of 43.5) are less leveraged (18.3%) than low climate risk firms (with an average CRIS rating of 23.5) (24.2%). Market leverage is also significantly lower for high versus low climate risk firms, even if the difference is smaller (13.4% versus 15.5%). High climate risk firms are larger and have more tangible assets, more R&D expenses, and a lower Tobin's Q than low climate risk firms. The results are similar when considering the Four Twenty Seven scores to disaggregate the sample between high climate risk (average Four Twenty Seven rating of 55.6) and low climate risk (average Four Twenty Seven rating of 29.8).

3.4. Bank loan and bond issuance data

We obtain bank loan data by using Dealscan and focus on loans with maturities greater than three years and amounts greater than $100 million. We use the item Margin(Bps) as our measure of the cost of the loan. Therefore, we exclude the observations for which this item is unavailable. We also exclude

[15] See here for more details.

the observations for which at least one of the independent variables used in our regressions is unavailable. This bank-loan level dataset is then matched with the data described in the previous sections. The correspondence between Dealscan and Compustat data is achieved with the linking database developed by Chava and Roberts (2008). Our total number of bank loan observations is 3,388.

Furthermore, we extract bond issuance data from Thomson-Reuters by focusing on vanilla, fixed-coupon bonds with an amount issued of at least $100 million. Bessembinder et al. (2018) define small corporate bonds as those with an issue size under $500 million. Helwege and Wang (2021) find that only 30% of bond issuances are under $292 million in 2002 dollars. For these reasons, and as our dataset covers the world's largest firms, our $100 million cutoff seems to be appropriate to gauge whether the decrease in leverage could come from a supply effect. In Dealscan, interest rates charged on bank loans are expressed in terms of basis points added to a reference rate (spreads). To draw a parallel between bank loans and bond issuances, we match our bond data from Thomson Reuters with the benchmark spread at issue reported in Bloomberg. To the best of our knowledge, this variable is the closest equivalent to Dealscan's spread. Our total number of bond issue observations is 5,105. The descriptive statistics are detailed in internet Appendix, Table IA1.

4. Empirical results

4.1. Leverage and climate risk

The descriptive statistics show that firms with high climate risk are less highly leveraged. It may be that firms with high climate risk are also the firms that find debt less valuable. However, as these firms are larger and have more tangible assets, the theory predicts that they should demand more debt, which suggests that they are not in a situation in which they would attach less value to debt. Based on the literature on capital structure determinants, we regress the firm's leverage on a set of firm characteristics, including credit ratings and climate risk measures. Clustering effects could bias the statistical significance of the results because of firm leverage persistence over time. Thus, in estimating our regressions, we apply the procedures described in Petersen (2009) to adjust the standard errors for clustering by firm. Our baseline regression is as follows:

$$LTDebt_{it} = \alpha + \beta_1 Climate\ risk_i + \beta_2 X_{it} + \beta_3 Z_{it} + \varepsilon_{it} \quad (1)$$

$LTDebt_{it}$ refers to our measure of long-term debt, either $BookLev_{it}$ or $MarketLev_{it}$, $Climate_i$ represents the value of the overall climate change risk exposure of a firm, X_{it} is a vector of controls that have been shown to affect the level of debt holdings and Z_{it} is a vector of fixed effects. $Climate\ risk$ is also interacted with $Post2015$, a dummy equal to one after 2015, to take into account the Paris Agreement effect. For these regressions, the equation is as follows:

$$LTDebt_{it} = \alpha + \beta_1 Climate\ risk_i + \beta_2 Climate\ risk_i * Post2015 + \beta_3 X_{it} + \beta_4 Z_{it} + \varepsilon_{it} \quad (2)$$

Our results are presented in Table 2 for book leverage and in Table 3 for market leverage. In Tables 2 and 3, CRIS data are used to measure climate risk in columns 1 to 5, whereas regressions in columns 6 to 10 use Four Twenty Seven data. Our findings confirm the previous work on capital structure. Firms with more tangible assets, as measured by a firm's property, plant, and equipment to total asset ratio, have a higher debt ratio. In contrast, intangible assets, as measured as research and development expenses scaled by total assets, reduce a firm's leverage. More profitable firms (EBIT/total assets) and firms with a higher proportion of operating expenses are less leveraged. Furthermore, by including country-industry fixed effects and year fixed effects (Table 2, columns 1, 2, 6 and 7), we can completely control for any determinant of leverage that is constant within a year or a pair industry-country. Thus, we control for any specific industry structure or regulation in a country. Alternatively, we apply a firm fixed effect regression to control for all time-invariant firm characteristics (Table 2, columns 3 and 8).

Controlling for these fundamental differences between firms, we find that increased physical climate risk reduces leverage for the whole period when using CRIS climate scores (Table 2, column 1). This result is not confirmed when using Four Twenty Seven data to measure climate risk (Table 2, column 6). The year 2015 was a pivotal year for considering climate risk that resulted from the Paris

Agreement (COP21) and the implementation of the TCFD. Therefore, we examine whether the impact of climate risk on leverage changed after 2015 by interacting our climate risk measure with a dummy variable equal to one for the post-2015 period. We find that the climate risk effect on leverage materializes mainly after 2015: a one standard deviation increase in climate risk reduces debt by 1.53% (-0.00139*10.833) with the CRIS score (column 2) or 1.38% (-0.00104*13.225) with the Four Twenty Seven score (column 7). This effect is economically significant, as it represents 6.91% of the leverage (CRIS scores) and 6.31% of the leverage (Four Twenty Seven scores).

Climate risk could also be a component of the overall corporate credit risk. If credit ratings already reflect climate risk, adding climate risk variables would not provide any additional information to the determinants of leverage. To verify that our climate risks measures are not mere proxies for credit risk, we add in all our regressions a variable that linearizes the credit ratings from 1 (D) to 20 (AAA) for firms that benefit from a rating and is zero otherwise. Firms with more favorable ratings have more long-term debt than poorly rated ones. Our findings may result from a reverse causality between credit rating and leverage. To address this potential problem, we use an instrumental variables approach. In the first stage, we estimate the endogenous variable (CreditRating) as a function of the exogenous variable in the second stage plus an additional instrument. Our credit rating variable instrument is based on its means for groups by year/sector/country. This instrument is correlated with our credit rating variable, although it is unlikely that the debt level of a given firm will depend on the average rating of the sector for a given year and country once fixed effects are considered. Our main results are confirmed, and the magnitude of the coefficients of the climate risk measure remains similar for book leverage (Table 2, columns 4 and 5 for CRIS, and columns 9 and 10 for Four Twenty Seven scores).

When market values are considered (Table 3), leverage increases with size and tangible assets and decreases with profitability, Tobin's Q, and the proportion of operational expenses, confirming the prior literature. Our main results remain similar, even if their amplitude is attenuated: a one standard deviation increase in climate risk decreases market leverage after 2015 by 0.59% to 0.65% (CRIS scores) or by 0.61% to 0.65% (Four Twenty Seven scores).

These findings suggest that our climate risk measures provide an additional risk factor that has an impact on leverage after 2015 and that is not already included in the credit risk ratings. After the strong signals sent to all participants in the financial system in 2015 regarding the necessity to develop climate-related disclosures and better understand their exposure to climate-related risks, both managers and investors became more aware of climate risks, which, in turn, can explain the reduction in leverage that we observe.

4.2. Difference-in-differences in leverage and climate risk: the Paris Agreement

Our analysis has thus far used continuous variables (CRIS or Four Twenty Seven scores) to explain firms' leverage. Our results identify a negative effect of physical climate risk on leverage concentrated in the post-2015 period, i.e., after the Paris Agreement. A first question arises about the possibility of our climate risk measure being endogenous. Our climate risk measures are both forward-looking measures that reflect the probability of future climate events that are highly exogenous. However, we acknowledge that this risk measure depends on the location of the firm's activities and the choice of business segments that are more or less vulnerable to climate risk, which are factors that may also impact the firm's leverage. To mitigate these potential endogeneity problems, we conduct additional tests in a difference-in-differences setting by using the 2015 Paris Agreement as a shock to firms, banks, and investors' awareness of physical climate risks. We define treatment variables based on our two climate risk scores. For each score, a firm is considered to belong to the treated group if the risk indicator has a value above the 60th percentile for the total sample (alternatively, within its industry). To form a control group, we use a one-to-one Mahalanobis matching method to match each firm in the treatment group to the nearest neighbor in the low climate risk control group (risk indicator below the 40th percentile). The matching is based on the values of EBIT, operating expenses, tangible assets, Tobin's Q, size, and book leverage before the Paris Agreement, or alternatively on the values of book leverage only. We then run our difference-in-differences analysis on the final sample of all treated and control firm-year observations during 2010-2019.[16] One clear advantage of the matching procedure is that

[16] We therefore combine DiD with matching on pre-treatment characteristics, as in Heckman et al. (1997).

parametric assumptions about the relationship between the outcome and control variables can be avoided.

Table 4 reports the results for the total sample (columns 1 and 2) and for the samples in which high climate risk firms are matched to low climate risk firms (columns 3 to 8). We define the group of companies with high climate risk either for the total sample (columns 1, 2, 5 and 6) or at the industry level (columns 3, 4, 7 and 8). All regressions include firm controls and firm and year fixed effects. The treatment effect is between -1.34% and -2.63% when defining the treatment with respect to the CRIS score (columns 1, 3, 5 and 7) and between -1.67% and -2.71% when using the Four Twenty Seven score to define the treated and control groups (columns 2, 4, 6 and 8). Overall, our results in a difference-in-differences setting are consistent with the patterns that we observe in our baseline tests (Table 2).

We assess the plausibility of the parallel trends assumption in two ways. First, we graphically plot the effect of climate risk on leverage over time. We regress leverage on the interaction of climate risk with year dummies after controlling for traditional determinants of leverage and firm and industry-year fixed effects. As internet Appendix Figure 1 depicts, the treatment effect is not statistically significantly different from zero in the entire pre-period, in line with the parallel trend hypothesis. It becomes significantly negative after 2015, confirming that this year is pivotal in the consideration of climate risk. Second, we compare changes in several firm characteristics between high and low climate risk firms over two pre-Paris Agreement periods, 2013-2014 and 2010-2014, for our two matching methods and when defining high climate risk for the total sample or at the industry level (internet Appendix Table IA2). High and low climate risk firms observe similar changes in EBIT, R&D expenses, Tobin's Q, and leverage over these two periods. When the matching is performed on leverage alone, high climate risk firms observe slightly smaller increases in size and operating expenses (Panel A). However, when we perform the matching on several firm characteristics, we do not find significantly different variations in the analysis variables (Panels B and C). Overall, these findings support the parallel trend assumption.

4.3. Climate risk and firm characteristics around the 2015 Paris Agreement

As descriptive statistics in Table 1, panel B, show, high climate risk firms are larger, less profitable, and have a smaller Tobin's Q. If these characteristics vary around the 2015 Paris Agreement, they may be driving our results that leverage decreases for high climate risk firms after 2015. In particular, one item of focus is the oil price, which fell by more than 50% between 2014 and 2016. The strong decrease in oil prices may reduce the debt capacity of firms highly exposed to variations in oil prices, for example, oil firms. Our tests would be contaminated if these firms were also exposed to high physical climate risk. Therefore, we include oil betas in all our regressions to account for firms' differentiated exposure to oil price changes. We also include an interaction term oil beta * post-2015 to account for the specific oil price pattern around the 2015 Paris Agreement. Our results in Table 5, columns 1 and 2 support our initial conclusion that climate risk, and not oil price, is the driving factor behind the reduction in leverage for high climate risk firms after 2015. Our results also remain similar when we exclude oil and gas industries (Table 5, columns 3 and 4) and when we split our sample into two subsamples depending on whether the oil beta is positive or negative (Table 5, columns 5 to 8).

We further investigate whether other variations in firm characteristics around the 2015 Paris Agreement may affect our results. We add to our regressions an interaction term among profitability, Tobin's Q, operational expenses, size, tangible assets, and the dummy variable post-2015. Internet Appendix, Table IA3, Panels A and B present the results that further support our conclusions that physical climate risks drive the negative impact on leverage after 2015.

4.4. Credit ratings and climate risk

We have seen in previous tests that the climate risk rating provides additional information compared to the credit rating to explain a firm's leverage after 2015. In this paragraph, we intend to explore the relationship between credit risk and climate risk in more detail. Credit ratings are fundamentally forward-looking; they are beliefs about the downside risks that surround promised future outcomes and the probability of financial distress. CRAs thus evaluate the fundamental drivers of creditworthiness over the long term. Climate change may affect creditworthiness through potential economic impact, physical damage to assets, and indirect impacts from supply chain disruption. Credit ratings should at least partially reflect climate risks, even if they do not consider them in their entirety. Rating agencies are multiplying the announcements related to environmental and climate risk factors, with a primary focus on sovereign and municipal bonds. For example, Moody's has changed its sovereign bond methodology to capture the effects of physical climate change in a broad set of rating factors that influence a sovereign's ability and willingness to repay its debt (Moody's, 2016). Over recent years, rating agencies have reinforced their expertise in climate risk rating by acquiring agencies specializing in corporate environmental performance ratings.

We acknowledge that credit ratings are not perfectly correlated with publicly observable and quantifiable information about firms' characteristics and that they bring a holistic creditworthiness assessment beyond financial and accounting ratios. Nevertheless, variables such as interest coverage, profitability, size, and risk measures are well-known determinants of rating levels and their corresponding expected default losses (see, for example, Standard and Poor's, 2013). To check whether credit ratings reflect climate risk, we estimate the following equation:

$$CreditRating_{it} = \alpha + \beta_1 Climate\ risk_i + \beta_2 X_{it} + \beta_3 Z_{it} + \varepsilon_{it} \tag{3}$$

$CreditRating_{it}$ refers to our linearized credit rating variable, $Climate\ risk_i$ represents the overall risk exposure of a firm, X_{it} is a vector of controls that have been shown to affect the level of credit ratings, and Z_{it} is a vector of fixed effects. $Climate\ risk$ is also interacted with the dummy $Post2015$. Table 6 presents our findings. We regress the credit rating variable on the following explanatory variables: profitability, interest coverage, size, age, Tobin's Q, working capital divided by total assets, operating expenses divided by total assets, R&D expenses divided by total assets, oil beta, and the fraction of tangible assets. We control for year fixed effects to consider that rating standards have tightened over time (see Jorion et al. 2009, Baghai et al. 2014), for country-industry fixed effects (as business risk varies across sectors and the sovereign rating represents in almost all cases a ceiling for the private sector) and firm fixed effects to control for time-invariant firm characteristics. As the results in Table 6 indicate, the coefficient of our climate risk variable is not significantly different from zero, either before or after 2015, whether using CRIS scores or Four Twenty Seven scores, which suggests that credit ratings do not reflect physical climate risk specific to the firm beyond the headquarters country climate risk that is captured by the country-industry dummies.

Accordingly, physical climate risk as measured by the CRIS or Four Twenty Seven ratings does not seem to be reflected in the credit ratings issued by the rating agencies, at least over the period that we examine.

4.5. Climate risk and leverage: demand or supply effect?

The observed level of debt is a function of a firm's demand for debt: the empirical capital structure literature traditionally assumes that in the absence of frictions, firms can borrow up to their optimum leverage, which depends on their characteristics. However, the reduction in leverage that we observe in the post-2015 period may also be the result of supply factors.

4.5.1. Climate risk and leverage: the demand effect

To adjust their leverage to climate risk, firms can reduce their demand for debt in line with the variation of their characteristics or issue new equity. We first examine whether firms subject to higher climate risk increase their net equity issuance (equity offerings minus repurchases). Table 7 presents our results. In columns (1) and (2), we use the CRIS climate risk score, and in columns (3) and (4), we use the Four Twenty Seven score. The results in columns (1) to (3) show a significantly positive coefficient associated with our variable climate risk*post-2015, suggesting that after 2015, net equity issuance increases with climate risk. The marginal effect of a one standard deviation increase in the climate risk after 2015 is between +0.19% and +0.25%.

An alternative way to examine the demand side is to focus on ESG performance. We first check whether our measure of climate risk is not a mere proxy for a more general ESG assessment. In Table 8, Panel A, we verify that our results remain unaffected after controlling for various ESG indicators. The regressions in columns (1) and (3) use the general ESG score given by the MSCI IVA ratings. The regressions in columns (2) and (4) use a dummy variable based on CDP data (carbon disclosure) that equals 1 if the firm is rated A (best grade) by CDP. Whatever the measure for ESG performance, our results on the impact of climate risk on leverage are qualitatively unchanged, which suggests that our climate risk measure is not a mere proxy for ESG performance.

On the other hand, environmental risk management expenses may allow firms to adapt their activities to climate risk and decrease operational risk. A reduction in operating leverage may be an alternative to a reduction in leverage. In Table 8, Panel B, we construct subsamples based on the values of the ESG variables. Columns 1 and 2 report the regressions conducted on firms with an above-median overall ESG score and firms with below or equal to the median overall ESG score, respectively. Only low ESG firms significantly reduce their leverage after 2015. In regressions (3) and (4), we split our sample between firms included and firms not included on CDP's A list. Firms on the A list have had a smaller decrease in their leverage ratio post-2015 compared to firms not on the A list. In columns (5) to (8), regressions are presented using the Four Twenty Seven score, and the results are similar. All differences between high ESG and low ESG firms are significant at the 1% level (except between columns (3) and (4), significant at the 10% level). Taken together, these results are consistent with the view that firms with better ESG scores are more likely to take proactive actions, for example, implementing appropriate risk management tools, to hedge their climate risk, thereby reducing the need for a decrease in their debt ratio.

4.5.2. Climate risk and leverage: the supply effect

To test whether supply factors are involved, we examine loan-level data that cover bond issues on the one hand and bank loans on the other hand. If a supply effect exists, the reluctance to finance high climate risk firms should materialize as higher spreads.

Climate risk and public debt markets

We first focus on the impact of physical climate risks on the cost of bonds. With the benchmark spread at issue as our measure of the cost of borrowing, we find a post-2015 rise in interest rates in bond markets. Columns (1) to (6) in Table 9 report the results. The effect is concentrated in high-risk firms. We find that post-2015, a one standard deviation increase in climate risk generates a 6.02 basis point increase (1.094*5.505= 6.02, with 5.505 being the standard deviation of the CRIS indicator within the high-risk group) in the spread at issue in the high-risk group when using CRIS scores (column 2) and a 9.82 basis point increase when using Four Twenty Seven scores (column 5). In both cases, we do not find any significant effect within the low-risk group, and the difference in the coefficients is significant between the two risk subgroups when using CRIS scores. In addition to firm and year fixed effects, we include fixed effects to account for the number of loans to the firm on the same date, loan purpose and secured/unsecured status. Our findings indicate a significant impact of physical climate risks on public debt cost in the post-2015 period.

Climate risk and bank loans

Table 10 reports the results for bank loans. Similar to bonds, the effect of climate risk in the post-2015 period is concentrated in high-risk firms. For these firms, the effect of a one standard deviation increase in climate risk, as measured by CRIS scores, is 23.37 basis points (Table 10, column 2). We do not find any significant effect within the low-risk group (column 3), and the difference in the coefficients between the two risk subgroups is significant. When using the Four Twenty Seven scores, the coefficient of our climate risk measure for high-risk firms is positive but insignificant. The Dealscan data are heavily biased toward the US (see Florou and Kosi, 2015). When we match our climate risk data with the Dealscan data, US firms represent 73% of bank loans compared to 39% in our main sample. In addition, the data matching process leads to the disappearance of a significant fraction of non-US high-risk firms for the Four Twenty Seven sample, especially after 2015. Therefore, we rerun our regressions for the US high-risk firm subsample (Table 10, columns 7 and 8). Our effect using the Four Twenty Seven score is significant at the 10% level.

Overall, our findings suggest that physical climate risks affect debt supply by increasing the cost of debt for high climate risk firms.

4.6. Robustness checks

We conduct several robustness checks using an alternative measure of physical climate risks, considering other fixed effects, the decomposition of climate risk in subrisks, and different horizons and scenarios. We also propose several tests to verify that our results reflect only physical climate risk, not transition risk.

Alternative measure of physical climate risk

Sautner et al. (2022) propose a method that identifies firm-level climate change exposure to climate change. They use transcripts of earnings conference calls by listed firms to build firm-year climate change measures. Their metrics include an overall exposure measure and topic-based measures, including a physical climate risk exposure measure, that we use in our tests. We re-estimate our basic regressions (equation 2). Table 11 reports our results that confirm previous findings with the CRIS and Four Twenty Seven climate risk measures.

Other fixed effects and controls

Our results are qualitatively unchanged when using country, industry, and year fixed effects (internet Appendix, Table IA4, columns 1 and 6). As an alternative to year fixed effects, we also add country-year fixed effects to control for variables that vary at the country-year level and could affect leverage, such as corporate taxes and the institutional characteristics of countries (Table IA4, columns 2 and 7). Including country-year and firm fixed effects also lead to similar results (columns 3 and 8). To consider the possibility of time effects that are specific to certain industries, we re-estimate our basic regressions, including industry-year fixed effects (columns 4 and 9) or industry-year and firm fixed effects (columns 5 and 10), and the results remain unchanged. We also rerun our regressions, including several dummy variables for each level of credit rating rather than our linearized variable, and our results remain. Finally, we rerun our main tests on a matched sample according to the methodology that was previously defined in our difference-in-differences tests around the Paris Agreement. Again, the results remain similar (Table IA5).

Quantile regressions

We also rerun our tests using quantile regressions. When compared to ordinary least square regression, quantile regression estimates have the advantage of being more robust against outliers. Further, unlike OLS regression, quantile regression does not assume a particular parametric distribution or a constant variance for our outcome variable, leverage. Internet Appendix Table IA6 presents the results of quantile regressions. We find that a 10-point increase in CRIS post-2015 climate risk lowers the 20th percentile of book leverage by 0.36% compared to 0.69% for the 80th percentile, confirming that climate risk reduces leverage after 2015, all the more so as the firm is more leveraged.

Acute risks and chronic risks

CRIS climate risk ratings combine information on the following seven direct climate hazards: three chronic hazards (increases in average temperature, changes in rainfall patterns, and sea level rise) and four acute hazards (heat waves, droughts, rainfall extremes, and storms). For each hazard, the rating is based on the analysis of information on the magnitude, duration, and frequency of the hazard (particularly relevant for acute hazards). To build a rating of 0 to 99 for each climate variable and each country, the relative changes are first extracted in the future time horizons compared to the historical reference period and then normalized across all scenarios and time horizons. These direct hazards are associated with information on the risk-aggravating context to capture indirect hazards. For example, the impact of heavy rainfall is larger when the proportion of high slopes in the area is high because of increased landslide risks, and extreme droughts lead not only to water scarcity but also to wildfires.

We examine the impact of each of these 7 climate subrisks on the leverage of firms. In equations (1) and (2), the overall climate risk variable is replaced by subrisk measures. Since the risk variables by category are normalized, their values are of the same magnitude as the overall rating. Therefore, the regression coefficients reflect the relative impact of the risk variables on debt but not the weight of each risk in the total risk to explain the climate impact on debt. The results in internet Appendix, Table IA7, Panel A, indicate that the four acute risks have a significant negative impact on leverage after 2015. After 2015, a one standard deviation increase in the subrisk rating is associated with a 1.53% decrease in the long-term book debt ratio for heavy rain risks, 1.41% for drought risks, 0.91% for heat wave risks and 1.38% for storms. Among chronic risks, sea level rise has an impact that is comparable to acute risks (1.17%), whereas temperature rise in itself has no impact on leverage. When the Four Twenty Seven scores are considered, the impact of subrisks is significant after 2015, with a magnitude of 1.22% for operating risks, 1.58% for floods, 0.96% for hurricanes and typhoons, and 1.27% for sea level rise (Table IA7, Panel B).

These results emphasize that the impact of aggregate climate risk on leverage is primarily because of the potential increase in the risks of extreme events on the 2030-2050 horizon.

Horizons and scenarios

One might be concerned that the two climate risk rating agencies use different scenarios to assess corporate risk. We verify that our results remain similar for alternative scenarios and horizons. We use low (RCP4.5) and high-intensity (RCP8.5) risks and consider the 2100 horizon rating as an alternative to our 2050 horizon and medium intensity (RCP6.0) CRIS climate risk rating. The results, reported in internet Appendix Table IA8, are qualitatively unchanged, although the coefficients of the variables change slightly depending on the chosen combination. Internet Appendix Table IA9 reports similar results for CRIS subrisks and alternative risk intensity and horizon.

Our tests show that CRAs do not appear to consider climate risk over the period studied. However, the rating agencies could be using other, more moderate scenarios than those considered in our study, which could explain our results. We replicate our regressions using the CRIS climate risk measure for the RCP4.5 scenario, and the results remain similar: we are unable to detect any effect of climate risk on credit ratings (internet Appendix, Table IA10).

Physical risk versus *transition risks*

We also verify that the results are robust to the exclusion of firms threatened by transition risks by running additional regressions excluding the 5 and 10 largest carbon-emitting industries identified in Ilhan et al. (2021). Our results that physical climate risk reduces leverage after 2015 remain similar (internet Appendix, Table IA11). We thus rule out the possibility that our findings account for transition risks rather than physical risks. Moreover, we verify that these results are not driven by some particular industries, as they remain qualitatively unchanged after the exclusion of the 5 or 10 most represented in-sample industries or after the elimination of the 5 most represented industries in each of the 2 risk-level groups. Our results are also similar when we rerun our tests for each industry group, constructed as in Kahle and Walking (1996), that has at least 1000 firm-year observations in our sample (internet Appendix, Table IA12).

Finally, to ensure that physical climate risk represents an additional effect when considered in addition to the transition risk, we also verify that our results remain similar when we add the Sautner et al. (2022) regulatory risk measure to the regressions, as well as its interaction with the dummy post-2015 (internet Appendix, Table IA13). These findings confirm that after 2015, leverage also decreases with the transition risk, but the effect of the physical climate risk remains unchanged.

5. Conclusion

In this paper, we analyze the impact of the climate risk rating on firms' leverage. We use forward-looking measures for physical climate risk at the firm level. Our work builds on the capital structure and climate risk literature. We find that firms exposed to greater climate risk are less leveraged in the post-2015 period, i.e., after the Paris Agreement (COP21) and the call from the Financial Stability Board for standard measures and disclosures of climate risks. We also show that the reduction in debt related to climate risk is shared between a demand effect and a supply effect. On the one hand, we find that, after 2015, increased climate risk lowers financial leverage and increases net equity issuance. The reduction in leverage is mainly observed for firms with low ESG performance, suggesting that high ESG firms are likely to take proactive actions to handle their climate risk rather than decrease their leverage. On the other hand, we find that the reduction in debt related to climate risk is at least partly due to a supply effect, as bondholders and bankers charge higher interest rates to high climate risk firms. Overall, our results suggest that over the recent period, climate risk has become an important factor in understanding the capital structure of firms.

Our findings offer several managerial implications. Despite the growing importance of climate change risks, accurate information about companies' exposure to climate change risks is still scarce. Our research emphasizes the importance of disclosing information about how physical climate risk affects corporate activity and what strategic actions firms take to manage and mitigate climate risks. The company must be able to think about the short-term and long-term consequences of climate change. For example, maintaining production lines in countries with high climate risk may be a short-term solution to minimize operating costs, but it may also have immediate and future consequences on the cost or access to financing. Similarly, the company may prefer to pay higher insurance premiums to address its climate risk but may also anticipate that this risk may no longer be insurable in the long term and choose to opt for other locations or strategies. The 2015 Paris Agreement was a warning signal to companies about the potential consequences of their exposure to climate risk on the value of their assets and their operating costs but also on their access to financing and the growing cost of debt.

Our analysis also supports the view that ESG performance protects firms from downside risk. Managers of firms exposed to high climate risks who can develop successful ESG strategies, for example, in terms of risk management, can generate tangible benefits for their firms in the form of better access to financing.

Our findings are also relevant for CRAs. Indeed, our results suggest that credit ratings do not reflect all the information related to physical climate risk over the period studied. These findings support the relevance of the strategy of several rating agencies that are developing their expertise in climate risks, notably through the acquisition of specialized agencies.

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Table 1

Descriptive statistics.

This table reports summary statistics. Panel A presents the descriptive statistics for the CRIS and the Four Twenty Seven climate variables. Each firm of the panel is covered by eight CRIS climate grades (an overall rating and seven subrisk ratings), and by five Four Twenty Seven climate grades (an overall rating and four subrisk ratings). In Panel B, descriptive statistics of various firm-year characteristics are reported for the total sample, the low climate risk (<40th percentile) and high climate risk (>60th percentile) observations. All variables are winsorized at the 1st and 99th percentiles, except for CreditRating. The statistics for CreditRating are presented for the firms that are credit rated. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999).

Panel A. Climate risks

CRIS					Four Twenty Seven				
	N	Mean	SD	Median		N	Mean	SD	Median
Climate risk	1,212	35.161	10.833	36.994	Climate risk	938	42.828	13.225	43.510
Heavy rainfall	1,212	37.305	15.796	36.382	OperationsRiskScore	938	38.247	10.146	36.210
Heat waves	1,212	31.828	10.562	30.511	Floods	938	23.615	7.946	22.330
Droughts	1,212	29.795	10.338	31.130	Sea level rise	938	11.130	9.114	8.790
Storms	1,212	44.197	15.096	46.349	HurricanesTyphoons	938	27.596	22.569	18.640
Sea level rise	1,212	41.663	13.984	46.943					
Temperature rise	1,212	23.873	8.940	23.735					
Rainfall patterns	1,212	16.168	6.989	16.569					

Panel B. Firm-year characteristics

	Total sample			Low climate risk firms, CRIS (<40th percentile)	High climate risk firms, CRIS (>60th percentile)	Low climate risk firms, 427 (<40th percentile)	High climate risk firms, 427 (>60th percentile)
	N	Mean	SD	Mean	Mean	Mean	Mean
BookLev	11,367	0.218	0.159	0.242	0.183	0.235	0.194
MarketLev	11,367	0.146	0.120	0.155	0.134	0.148	0.142
EBIT	11,367	0.092	0.070	0.101	0.083	0.099	0.080
Log Age	11,367	2.694	1.472	2.417	2.973	2.443	3.471
TobinQ	11,367	1.986	1.433	2.161	1.786	2.261	1.692
OpEx	11,367	0.691	0.529	0.773	0.629	0.762	0.624
R&DExp	11,367	0.020	0.036	0.013	0.029	0.017	0.027
PPE	11,367	0.297	0.236	0.255	0.323	0.266	0.336
LogTotAssets	11,367	9.376	1.214	9.267	9.458	9.520	9.578
Oil beta	11,367	0.019	0.152	0.003	0.030	0.019	0.015
CreditRating	7,602	12.279	2.858	11.732	12.992	11.954	13.001
Log IntCoverage	11,058	2.689	1.717	2.512	3.040	2.358	3.079
WorkCap	11,367	0.131	0.172	0.105	0.166	0.099	0.158
CSR	8,598	3.273	1.572	3.221	3.369	3.317	3.205
CDP A list	6,759	0.143	0.350	0.132	0.159	0.149	0.154

Table 2

Climate risk and long-term debt: book leverage.

This table presents estimates of the effects of overall climate risk on the level of long-term debt using BookLev as the dependent variable. Columns (1) to (5) report estimates using the CRIS measure of climate risk. Columns (6) to (10) report estimates using the Four Twenty Seven measure of climate risk. Columns (1), (2), (3), (6), (7), and (8) report OLS estimates. Columns (4), (5), (9), and (10) report 2SLS estimates, where average values of CreditRating at the country-industry-year level are instruments for CreditRating. Regressions (1), (2), (4), (6), (7), and (9) include country-industry and year fixed effects. Regressions (3), (5), (8), and (10) include firm and year fixed effects. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev	(7) BookLev	(8) BookLev	(9) BookLev	(10) BookLev
		CRIS – OLS		CRIS – 2SLS			Four Twenty Seven - OLS		Four Twenty Seven – 2SLS	
Climate risk	-0.00154**	-0.000969		-0.000658		0.000625	0.00105		0.000790	
	(-2.304)	(-1.451)		(-1.005)		(0.848)	(1.417)		(1.009)	
Climate risk*Post2015		-0.00139***	-0.00134***	-0.00140***	-0.00136***		-0.00104***	-0.000904***	-0.000964***	-0.000915***
		(-5.641)	(-5.365)	(-5.983)	(-5.752)		(-5.008)	(-4.307)	(-4.800)	(-4.584)
EBIT	-0.204***	-0.201***	-0.327***	-0.314***	-0.328***	-0.204***	-0.201***	-0.331***	-0.322***	-0.332***
	(-3.546)	(-3.485)	(-7.523)	(-7.786)	(-7.974)	(-3.292)	(-3.238)	(-6.561)	(-6.877)	(-6.964)
Log Age	-0.00177	-0.00188	0.00235	-7.20e-05	0.00391	-0.00576	-0.00608	0.00648	0.00203	0.00787
	(-0.501)	(-0.530)	(0.313)	(-0.0157)	(0.541)	(-1.461)	(-1.537)	(0.738)	(0.367)	(0.931)
TobinQ	-0.00143	-0.00153	0.00637**	0.00547**	0.00632**	0.000978	0.000858	0.00764**	0.00714**	0.00763**
	(-0.472)	(-0.504)	(2.244)	(2.096)	(2.347)	(0.279)	(0.245)	(2.209)	(2.243)	(2.322)
OpEx	-0.0444***	-0.0445***	-0.0414***	-0.0416***	-0.0414***	-0.0448***	-0.0453***	-0.0536***	-0.0533***	-0.0535***
	(-3.990)	(-4.007)	(-3.275)	(-4.008)	(-3.466)	(-3.529)	(-3.559)	(-3.761)	(-4.510)	(-3.972)
R&DExp	-0.490***	-0.494***	-0.168*	-0.235***	-0.165*	-0.362***	-0.364***	-0.143	-0.190*	-0.142
	(-4.292)	(-4.331)	(-1.660)	(-2.618)	(-1.723)	(-2.974)	(-2.985)	(-1.322)	(-1.957)	(-1.381)
Log TotAssets	-0.000553	-0.000900	0.0212***	0.0173***	0.0217***	0.00108	0.00102	0.0231***	0.0183***	0.0236***
	(-0.138)	(-0.225)	(3.045)	(3.481)	(3.307)	(0.252)	(0.239)	(2.946)	(3.159)	(3.186)
PPE	0.112***	0.112***	0.180***	0.170***	0.181***	0.0876**	0.0876**	0.210***	0.190***	0.211***
	(3.714)	(3.721)	(4.665)	(5.464)	(4.988)	(2.360)	(2.357)	(5.003)	(5.411)	(5.320)
Oil beta	0.000972	0.000738	-0.0144	-0.0145	-0.0148	-0.000173	-0.000459	-0.0100	-0.0107	-0.0106
	(0.0645)	(0.0489)	(-1.167)	(-1.252)	(-1.267)	(-0.0107)	(-0.0284)	(-0.782)	(-0.884)	(-0.869)
CreditRating	0.00218***	0.00217***	0.000417	-0.000630	-0.000674	0.00241***	0.00238***	0.000959	0.000175	8.64e-05
	(3.337)	(3.320)	(0.670)	(-0.766)	(-0.838)	(3.339)	(3.297)	(1.431)	(0.169)	(0.0858)
Constant	0.125**	0.109*	-0.00256	-0.0931	-0.00368	0.0327	0.0149	-0.0449	-0.189**	-0.0466
	(2.194)	(1.906)	(-0.0356)	(-1.273)	(-0.0545)	(0.526)	(0.239)	(-0.549)	(-2.443)	(-0.604)
Observations	11,367	11,367	11,367	11,367	11,367	8,933	8,933	8,933	8,933	8,933
R-squared	0.513	0.515	0.848			0.522	0.524	0.844		
Country-Industry Fixed Effects	Yes	Yes		Yes		Yes	Yes		Yes	
Firm Fixed Effects			Yes		Yes			Yes		Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3

Climate risk and long-term debt: market leverage.

This table presents estimates of the effects of overall climate risk on the level of long-term debt using MarketLev as the dependent variable. Columns (1) to (5) report estimates using the CRIS measure of climate risk. Columns (6) to (10) report estimates using the Four Twenty Seven measure of climate risk. Columns (1), (2), (3), (6), (7), and (8) report OLS estimates. Columns (4), (5), (9), and (10) report 2SLS estimates, where average values of CreditRating at the country-industry-year level are instruments for CreditRating. Regressions (1), (2), (4), (6), (7), and (9) include country-industry and year fixed effects. Regressions (3), (5), (8), and (10) include firm and year fixed effects. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) MarketLev	(2) MarketLev	(3) MarketLev	(4) MarketLev	(5) MarketLev	(6) MarketLev	(7) MarketLev	(8) MarketLev	(9) MarketLev	(10) MarketLev
		CRIS – OLS		CRIS – 2SLS			Four Twenty Seven - OLS		Four Twenty Seven – 2SLS	
Climate risk	-0.00105**	-0.000804*		-0.000685		0.000177	0.000381		0.000273	
	(-2.429)	(-1.842)		(-1.593)		(0.354)	(0.757)		(0.553)	
Climate risk*Post2015		-0.000597***	-0.000542***	-0.000576***	-0.000545***		-0.000494***	-0.000460***	-0.000481***	-0.000462***
		(-3.588)	(-3.203)	(-3.624)	(-3.388)		(-3.338)	(-2.928)	(-3.250)	(-3.091)
Observations	11,367	11,367	11,367	11,367	11,367	8,933	8,933	8,933	8,933	8,933
R-squared	0.595	0.596	0.859			0.617	0.618	0.862		
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry Fixed Effects	Yes	Yes		Yes		Yes	Yes		Yes	
Firm Fixed Effects			Yes		Yes			Yes		Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4

Difference-in-differences in leverage around the year 2015.

This table presents difference-in-differences estimates for the leverage before and after 2015, using BookLev as the dependent variable. All regressions report estimates using as independent variables the interaction between Post2015 and a dummy variable equal to 1 if the climate risk indicator is above the 60th percentile and 0 if the climate risk indicator is below the 40th percentile. Columns (1) and (2) use the total sample, comprising all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). The regressions are conducted on all firm-year observations except those between the 40th and the 60th percentiles of the climate risk indicator. Columns (3) and (4) use a matched sample, in which each high climate risk firm (>60th percentile within the industry group, using CRIS) is matched to a low climate risk firm (<40th percentile within the industry group using CRIS) based on the 2015 value of the book leverage, with a caliper of 0.02. Columns (5) to (8) use a matched sample, in which each high-risk firm is matched to a low-risk firm, using 2010, 2013, and 2015 values of BookLev, EBIT, TobinQ, OpEx, Log TotAssets, and PPE. Columns (5) and (6) define the 40th and 60th percentiles with respect to the total sample. Columns (7) and (8) define the 40th and 60th percentiles within each industry group. Regressions (1), (3), (5), and (7) report estimates using the CRIS measure of climate risk. Regressions (2), (4), (6), and (8) report estimates using the Four Twenty Seven measure of climate risk. The matchings are conducted using a one-to-one Mahalanobis matching with replacement. Industry groups are defined as in Kahle and Walkling (1996). All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev	(7) BookLev	(8) BookLev
Climate risk measure	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven
HighClimateRisk*Post2015	-0.0220***	-0.0258***	-0.0263***	-0.0271***	-0.0134**	-0.0221***	-0.0152**	-0.0167**
	(-3.723)	(-3.826)	(-3.120)	(-2.770)	(-2.067)	(-2.595)	(-2.534)	(-1.976)
Observations	9,080	7,136	3,945	3,173	6,268	4,105	6,260	4,090
R-squared	0.855	0.844	0.865	0.842	0.850	0.851	0.886	0.880
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5

Climate risk, long-term debt, and fossil fuel dependency.

This table presents estimates of the effects of overall climate risk on long-term debt after accounting for fossil fuel dependency. Columns (1), (3), (5), and (7) report estimates using the CRIS measure of climate risk. Columns (2), (4), (6), and (8) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (2) control for the interaction between Post2015 and Oil beta. Regressions (3) and (4) exclude firms belonging to Oil & Gas Extraction (SIC 1300-1399) and Petroleum & Coal Products (SIC 2900-2999) industries. Regressions (5), (6), (7), and (8) report estimates conducted on subsamples based on the values of Oil beta. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev	(7) BookLev	(8) BookLev
	Control for Oil beta*Post2015		Exclude SIC13 & SIC29		Oil beta ≥0		Oil beta<0	
Climate risk measure	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven
Climate risk*Post2015	-0.00137***	-0.000904***	-0.00131***	-0.000875***	-0.00135***	-0.000920***	-0.000767*	-0.000743**
	(-5.474)	(-4.307)	(-5.153)	(-4.017)	(-3.884)	(-3.060)	(-1.878)	(-2.010)
Oil beta	-0.0280**	-0.0112	-0.0157	-0.00974	-0.000692	-0.00106	-0.0199	-0.0146
	(-1.965)	(-0.752)	(-1.219)	(-0.728)	(-0.0363)	(-0.0441)	(-0.673)	(-0.452)
Oil beta*Post2015	0.0392**	0.00347						
	(1.996)	(0.170)						
Observations	11,367	8,933	10,790	8,475	6,764	5,044	4,603	3,889
R-squared	0.848	0.844	0.850	0.846	0.863	0.860	0.890	0.885
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6

Credit rating and climate risk.

This table presents estimates of the effects of overall climate risk on credit rating. The regressions use CreditRating as the dependent variable for firm-year observations with a credit rating. Columns (1) to (3) report estimates using the CRIS measure of climate risk. Columns (4) to (6) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1), (2), (4), and (5) include country-industry and year fixed effects. Regressions (3) and (6) include firm and year fixed effects. All regressions exclude observations with missing Log IntCoverage. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) CreditRating	(2) CreditRating	(3) CreditRating	(4) CreditRating	(5) CreditRating	(6) CreditRating
Climate risk measure		CRIS			Four Twenty Seven	
Climate risk	0.00924	0.00781		-0.0255	-0.0264	
	(0.734)	(0.620)		(-1.560)	(-1.581)	
Climate risk*Post2015		0.00321	-0.00231		0.00189	0.00289
		(0.692)	(-0.578)		(0.492)	(0.848)
EBIT	6.872***	6.862***	3.667***	7.091***	7.087***	3.946***
	(4.021)	(4.011)	(4.201)	(4.039)	(4.034)	(4.134)
Log Age	0.315***	0.315***	0.203*	0.410***	0.410***	0.247*
	(3.589)	(3.590)	(1.708)	(3.783)	(3.781)	(1.789)
TobinQ	0.183**	0.184**	0.0950*	0.138	0.139	0.108**
	(2.138)	(2.145)	(1.856)	(1.635)	(1.637)	(2.024)
OpEx	0.138	0.138	0.355**	0.129	0.129	0.458**
	(0.613)	(0.613)	(2.229)	(0.465)	(0.466)	(2.557)
R&DExp	-2.140	-2.121	2.064*	-3.937	-3.924	1.943*
	(-0.805)	(-0.796)	(1.954)	(-1.514)	(-1.505)	(1.827)
Log TotAssets	1.123***	1.124***	0.713***	1.122***	1.122***	0.816***
	(11.40)	(11.39)	(6.055)	(10.37)	(10.37)	(5.942)
PPE	-0.224	-0.225	2.794***	0.407	0.407	3.664***
	(-0.378)	(-0.379)	(4.911)	(0.575)	(0.575)	(5.910)
Oil beta	-1.781***	-1.784***	-0.390*	-1.689***	-1.689***	-0.336*
	(-5.425)	(-5.424)	(-1.860)	(-4.579)	(-4.578)	(-1.716)
Log IntCoverage	0.458***	0.458***	0.0619	0.408***	0.408***	0.0474
	(5.510)	(5.512)	(1.440)	(4.563)	(4.564)	(1.018)
WorkingCap	1.487*	1.478*	0.923**	1.856**	1.851**	1.257***
	(1.914)	(1.899)	(2.201)	(2.218)	(2.206)	(3.148)
Constant	-0.915	-0.876	2.876**	0.250	0.287	1.473
	(-0.634)	(-0.607)	(2.391)	(0.157)	(0.179)	(1.027)
Observations	7,602	7,602	7,602	6,326	6,326	6,326
R-squared	0.556	0.556	0.915	0.541	0.541	0.910
Country-Industry Fixed Effects	Yes	Yes		Yes	Yes	
Firm Fixed Effects	No	No	Yes	No	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 7

Climate risk and equity issuances.

This table presents estimates of the effects of overall climate risk on the level of equity issuances, using NetEquityIssued as the dependent variable. Columns (1) and (2) report estimates using the CRIS measure of climate risk. Columns (3) and (4) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (3) include country-industry and year fixed effects. Regressions (2) and (4) include firm and year fixed effects. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) NetEquityIssued	(2) NetEquityIssued	(3) NetEquityIssued	(4) NetEquityIssued
Climate risk measure	CRIS		Four Twenty Seven	
Climate risk	0.0148		0.0125	
	(0.913)		(0.816)	
Climate risk*Post2015	0.0231***	0.0177**	0.0174***	0.00978
	(2.963)	(2.207)	(2.711)	(1.483)
Observations	11,367	11,367	8,933	8,933
R-squared	0.422	0.602	0.444	0.617
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Country-Industry Fixed Effects	Yes		Yes	
Firm Fixed Effects	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table 8

Climate risk, long-term debt, and corporate social responsibility (CSR).

Panel A reports OLS estimates of the effects of overall climate risk on long-term debt after controlling for CSR. Columns (1) and (2) report estimates using the CRIS measure of climate risk. Columns (3) and (4) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (3) use CSR Score as measure of CSR. Regressions (2) and (4) use the presence of the firm on the CDP A list as the measure of CSR. Panel B reports estimates of the effects of overall climate risk on long-term debt, for the analysis of subsamples based on the values of CSR variables. Columns (1) to (4) report estimates using the CRIS measure of climate risk. Columns (5) to (8) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1), (2), (5), and (6) report estimates conducted on subsamples based on the values of the CSR Score. Regressions (3), (4), (7), and (8) report estimates conducted on subsamples based on the presence of the firm on the CDP A list. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. Climate risk and long-term debt, when controlling for CSR

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev
Climate risk measure	CRIS		Four Twenty Seven	
Climate risk*Post2015	-0.00102***	-0.00120***	-0.000674***	-0.000851***
	(-4.203)	(-3.944)	(-3.233)	(-3.188)
CSR Score	-0.000988		-0.000995	
	(-0.763)		(-0.712)	
CDP A list		0.00180		0.00311
		(0.554)		(0.907)
Observations	8,598	6,759	6,951	5,557
R-squared	0.879	0.887	0.875	0.877
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Panel B. Climate risk and long-term debt, subsamples based on CSR variables

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev	(7) BookLev	(8) BookLev
Climate risk measure	CRIS				Four Twenty Seven			
Subsamples	CSR Score above median	CSR Score below median	In CDP's A list	Not in CDP's A list	CSR Score above median	CSR Score below median	In CDP's A list	Not in CDP's A list
Climate risk*Post2015	-0.000345	-0.00159***	-0.000270	-0.00136***	-2.36e-05	-0.00136***	0.000504	-0.00108***
	(-1.139)	(-4.301)	(-0.423)	(-3.823)	(-0.0976)	(-3.823)	(0.993)	(-3.474)
Observations	3,875	4,723	964	5,795	3,112	3,839	872	4,685
R-squared	0.901	0.887	0.930	0.891	0.898	0.885	0.928	0.882
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9

Climate risk and cost of bond loans.

This table presents OLS estimates of the effects of overall climate risk on the cost of bond loans, using Spread as the dependent variable. Columns (1) to (3) report estimates using the CRIS measure of climate risk. Columns (4) to (6) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (4) are conducted on the total sample. Regressions (2) and (5) cover the high risk companies with a climate risk rating above the 60th percentile and regressions (3) and (6) cover the low risk companies with a climate risk rating below the 40th percentile. All regressions include firm, loan characteristics (seniority, number of loans to the company on the same date, loan purpose, secured/unsecured status), and year fixed effects. Appendix A presents variable definitions. The total sample comprises all vanilla fixed-coupon bond loans over $100 million with a maturity of more than 3 years granted to firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) Spread	(2) Spread	(3) Spread	(4) Spread	(5) Spread	(6) Spread
Climate risk measure		CRIS			Four Twenty Seven	
Sample	Total sample	High risk	Low risk	Total sample	High risk	Low risk
Climate risk*Post2015	0.389	1.094**	-0.980	-0.0878	1.266**	-0.0202
	(1.231)	(2.181)	(-1.195)	(-0.269)	(2.162)	(-0.0168)
Log Amount	2.422	12.01***	-2.394	4.982	10.06**	-1.257
	(0.682)	(3.181)	(-0.352)	(1.410)	(2.436)	(-0.187)
Log Maturity	25.28***	21.11***	28.10***	26.06***	25.53***	28.56***
	(13.76)	(6.533)	(10.91)	(15.02)	(10.51)	(10.55)
EBIT	-397.1***	-519.2***	-170.6	-345.9***	-420.5***	-388.6**
	(-5.049)	(-4.491)	(-0.977)	(-4.722)	(-3.827)	(-2.441)
Log Age	-34.04***	-22.99	-26.84***	-36.70***	-68.87	-33.62***
	(-4.173)	(-0.851)	(-3.702)	(-4.442)	(-1.173)	(-4.022)
TobinQ	-5.218	6.312	-12.85	-4.553	11.99*	-8.464
	(-0.767)	(0.865)	(-0.926)	(-0.746)	(1.818)	(-0.735)
OpEx	-4.302	-34.48	5.846	-20.18	-9.549	-58.11***
	(-0.244)	(-0.874)	(0.269)	(-1.124)	(-0.264)	(-2.764)
R&DExp	-175.5*	-336.7**	-65.99	-140.5	-286.4**	60.76
	(-1.894)	(-2.088)	(-0.340)	(-1.586)	(-2.186)	(0.303)
Log TotAssets	-32.67***	-58.88***	-14.42	-28.64***	-29.23*	-43.49**
	(-3.000)	(-3.358)	(-0.995)	(-2.616)	(-1.714)	(-2.158)
PPE	-36.84	-179.7	52.93	-34.20	-66.85	-2.876
	(-0.675)	(-1.642)	(0.681)	(-0.649)	(-0.710)	(-0.0337)
Oil beta	-26.53	3.092	-71.24*	-12.45	-2.619	-22.37
	(-1.127)	(0.138)	(-1.811)	(-0.705)	(-0.0835)	(-0.935)
CreditRating	-4.088**	-3.309	-2.891	-3.934**	-5.043**	-4.650
	(-2.170)	(-1.270)	(-1.147)	(-2.062)	(-2.109)	(-1.617)
Constant	519.8***	599.3**	342.1	420.2***	441.1*	759.5***
	(3.324)	(2.538)	(1.401)	(2.621)	(1.812)	(2.719)
Observations	5,105	1,757	2,101	4,565	1,540	1,903
R-squared	0.836	0.848	0.834	0.806	0.854	0.809
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 10

Climate risk and cost of bank loans.

This table presents estimates of the effects of overall climate risk on the cost of bank loans using Spread as the dependent variable. Columns (1), (2), (3), and (7) report estimates using the CRIS measure of climate risk. Columns (4), (5), (6), and (8) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (4) are conducted on the total sample. Regressions (2), (5), (7), and (8) cover the high risk companies with a climate risk rating above the 60th percentile and regressions (3) and (6) cover the low risk companies with a climate risk rating below the 40th percentile. Regressions (7) and (8) focus on US firms. All regressions include firm, loan characteristics (loan and repayment types, seniority, number of loans to the company on the same date, loan purpose, secured/unsecured status), and year fixed effects. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, CreditRating, Log Amount, and Log Maturity. Appendix A presents variable definitions. Appendix A presents variable definitions. The total sample comprises all bank loans over $100 million with a maturity of more than 3 years granted to firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) Spread	(2) Spread	(3) Spread	(4) Spread	(5) Spread	(6) Spread	(7) Spread	(8) Spread
Climate risk measure		CRIS			Four Twenty Seven		CRIS	Four Twenty Seven
Sample	Total sample	High risk	Low risk	Total sample	High risk	Low risk	High risk (USA only)	High risk (USA only)
Climate risk*Post2015	0.0779	4.245**	-0.000824	0.0441	0.642	-0.639	4.787***	1.640*
	(0.277)	(2.053)	(-0.00153)	(0.163)	(0.561)	(-1.271)	(2.681)	(1.820)
Observations	3,388	1,009	1,467	2,873	879	1,317	663	751
R-squared	0.797	0.794	0.820	0.793	0.825	0.835	0.821	0.810
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11

Climate risk and long-term debt: alternative climate risk measure.

This table presents estimates of the effects of climate risk on the level of long-term debt, using the Sautner et al. (2020) climate risk measure. Columns (1), (2) and (3) report OLS estimates. Columns (4) and (5) report 2SLS estimates, where average values of CreditRating at the country-industry-year level are instruments for CreditRating. Regressions (1), (2) and (4) include country-industry and year fixed effects. Regressions (3) and (5) include firm and year fixed effects. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev
		OLS		2SLS	
Climate risk	-0.0353**	-0.00207	0.0139	0.0137	0.0145
	(-2.160)	(-0.0869)	(0.952)	(0.963)	(1.058)
Climate risk*Post2015		-0.0560**	-0.0600**	-0.0607***	-0.0604***
		(-2.083)	(-2.489)	(-2.624)	(-2.674)
Observations	8,770	8,770	8,770	8,770	8,770
R-squared	0.468	0.468	0.841		
Constant	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Country-Industry Fixed Effects	Yes	Yes	No		
Firm Fixed Effects	No	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Appendix A. Variable Definitions

Variable	Description
BookLev	Ratio of long-term debt to book assets. DLTT/AT in Compustat.
CDP A list	Equals one if the company is rated A by CDP. Set to missing if the company was not questioned by CDP.
Climate risk	CRIS global risk grade for the median scenario, 2050 time-horizon (except in Table IA8, where alternative horizons and scenarios are used), Four Twenty Seven global risk grade, or physical risk as measured by the variable $CCExposurePhy$ $(\times 10^3)$ in Sautner et al. (2020). Sources Carbone 4, March 2018, Four Twenty Seven, November 2020, and Sautner et al. (2020).
CreditRating	This variable is based on the S&P Long-term Issuer Rating when available. If not available, we rely on Moody's Long-term Issuer Rating and eventually on the Fitch Long-term Issuer Default Rating if neither of the first two measures is available. Similar to Baghai et al. (2014), we linearize these ratings from 1 to 20, with 20 being the best rating. Missing ratings are coded as 0.
CSR Score	IVA Company Rating given in MSCI IVA ratings, converted from 0 for the worst grade (CCC) to 6 for the best grade (AAA).
Droughts	CRIS drought risk grade for the median scenario, 2050 time-horizon (except in Table IA9, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
EBIT	Ratio of EBIT to book assets. EBIT/AT in Compustat.
Floods	Four Twenty Seven flood risk grade. Source Four Twenty Seven, November 2020.
Heavy rainfall	CRIS heavy rainfall risk grade for the median scenario, 2050 time-horizon (except in Table IA9, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
Heat waves	CRIS heat wave risk grade for the median scenario, 2050 time-horizon (except in Table IA9, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
HighClimateRisk	Equals one for firms with climate risk above the 60th percentile and 0 for firms below the 40th percentile. Set to missing between the 40th and 60th percentiles.
HurricanesTyphoons	Four Twenty Seven hurricane and typhoon risks. Source Four Twenty Seven, November 2020.
Log Age	Natural logarithm of the difference between the year of observation and the initial public offering year (using IPODATE in Compustat). If the Names file[18] indicates a higher age, we substitute the previous measure with the Names file number.
Log Amount	Natural logarithm of the amount borrowed, expressed in US dollars. Corresponds to Amount Issued (USD) in Thomson-Reuters and to Tranche Amount Converted (m)(USD) multiplied by 1 million in Dealscan.
Log IntCoverage	Natural logarithm of the ratio of EBIT to interest expenses. EBIT/XINT in Compustat.
Log Maturity	Natural logarithm of the maturity expressed in months. Corresponds to the number of months between issue date and maturity in Thomson-Reuters, and between tranche active date and tranche maturity date in Dealscan.
Log TotAssets	Natural logarithm of book assets (AT in Compustat). Book asset amounts are converted to US dollars using the year-end exchange rates from the OECD data portal[19]
MarketLev	Long-term debt divided by the sum of the year-end market capitalization and the difference between book asset value and common/ordinary equity. DLTT/(AT-CEQ+PRCC_F*CSHO) in Compustat North America DLTT/(AT-CEQ+PRCCD*CSHOC) in Compustat Global.
NetEquityIssued	Ratio of net equity issued to book assets. (SSTK-PRSTKC)/AT in Compustat, multiplied by 100.
Oil beta	Sensitivity of monthly stock returns to monthly oil (WTI) returns after controlling for monthly market (MSCI World) returns. Similar to Ilhan et al. (2021), we compute the sensitivity for each month with a rolling window of 60 months. For each firm i, the variable corresponds to the β_2 coefficient in the regression $Returns_{it} = Constant + \beta_1 Market\ returns_t + \beta_2 Oil\ returns_t$. The value of β_2 is then averaged over the year.
OperationsRiskScore	Four Twenty Seven operations risk grade. Source Four Twenty Seven, November 2020.
OpEx	Ratio of operational expenses to book assets. XOPR/AT in Compustat.
Post2015	Equals one for observations after 2015 and zero otherwise.
PPE	Ratio of net tangible assets to book assets. PPENT/AT in Compustat.
Rainfall patterns	CRIS rainfall pattern risk grade for the median scenario, 2050 time-horizon (except in Table IA9, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
R&DExp	Ratio of R&D expenses to book assets. XRD/AT in Compustat.
Regulatory risk	Climate regulatory risk as measured by the variable $CCExposureReg$ $(\times 10^3)$ in Sautner et al. (2020).
Sea level rise	CRIS sea level rise risk grade for the median scenario, 2050 time-horizon (except in Table IA9, where alternative horizons and scenarios are used), or Four Twenty Seven sea level rise risk grade. Sources Carbone 4, March 2018, and Four Twenty Seven, November 2020.
Spread	For bonds: benchmark yield at issue in Bloomberg. For bank loans: Margin (Bps), in Dealscan.
Storms	CRIS storm risk grade for the median scenario, 2050 time-horizon (except in Table IA9, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
Temperature rise	CRIS rise in average temperature risk grade for the median scenario, 2050 time-horizon (except in Table IA9, where alternative horizons and scenarios are used). Source Carbone 4, March 2018.
TobinQ	Ratio of the sum of the year-end market capitalization and the difference between book asset value and common/ordinary equity to book asset value. (AT-CEQ+PRCC_F*CSHO)/AT in Compustat North America, (AT-CEQ+PRCCD*CSHOC)/AT in Compustat Global.
WorkingCap	Ratio of working capital to book assets. WCAP/AT in Compustat

[18] https://wrds-web.wharton.upenn.edu/wrds/tools/variable.cfm?library_id=129&file_id=65815
[19] https://data.oecd.org/conversion/exchange-rates.htm

Appendix B. Description of the CRIS and Four Twenty Seven datasets

	CRIS	Four Twenty Seven
General overview	CRIS ratings capture the increase in risk due to the increase in intensity or frequency of the climate-related hazards in the future due to global warming. They do not capture the absolute risk from future climate or weather. Scores range from 0 to 99. The higher the score, the higher the risk. Each company receives one rating, with the assumption that a company's climate exposure is stable over a few years.	Four Twenty Seven ratings capture both historical risks and the increase in intensity or frequency of the climate-related hazards in the future. Scores range from 0 to 100. The higher the score, the higher the risk. Each company receives one rating, with the assumption that a company's climate exposure is stable over a few years.
Risks covered	The climate risk score aggregates the scores of 7 subrisks: • 4 acute risks ○ Increase in droughts ○ Increase in heatwaves ○ Increase in storms ○ Increase in heavy rainfalls • 3 chronic risks ○ Increase in average temperature ○ Changes in rainfall patterns ○ Increase in sea levels The rating assigned to each subrisk is normalized to range between 0 and 99. The climate risk score is a weighted geometric mean of the 7 subrisks, with more weight given to acute risks.	The climate risk score aggregates the scores of 3 subrisks: • Operations risk (70% of the total), including: ○ Historical and future floods ○ Increase in sea levels ○ Historical hurricane and typhoon risk • Supply chain risk (15%) • Market risk (15%) The rating assigned to each subrisk is normalized to range between 0 and 100. The climate risk score is an arithmetic average of the 3 subrisks.
Climate scenarios used	All subrisks rely on the Representative Concentration Pathways (RCP)[20] from the Intergovernmental Panel on Climate Change (IPCC): • Low-emission scenario (RCP 4.5) • Medium-emission scenario (RCP 6.0) • High-emission scenario (RCP 8.5)	Historical data and high-emission scenario (RCP 8.5). Historical hurricane and typhoon risk is the only subrisk that does not rely on projections. All the other subrisks integrate a forward-looking approach and use the RCP 8.5 as a reference for projections. Four Twenty Seven considers that the impacts of the different RCPs are similar before 2050.[21]
Scoring principles	For each company, CRIS identifies the industries and locations of the activities. This information is generally obtained from the firm's annual reports. Industry information	The sectoral breakdown of the activities is determined using revenues. For each climate hazard, Four Twenty Seven determines sector-specific sensitivity levels. The location of a

[20] The RCPs include a stringent mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0) and one scenario with very high GHG emissions (RCP8.5). Scenarios without additional efforts to constrain emissions ("baseline scenarios") lead to pathways that range between RCP6.0 and RCP8.5. Currently, the RCP2.6 scenario feasibility is seriously in question. Therefore, the CRIS measures rely on the RCP4.5 (low), RCP6.0 (medium) and RCP8.5 (high) scenarios. See IPCC AR5.

[21] The IPCC report underlines that the likelihood of individual scenarios is not part of the assessment. There is considerable uncertainty about the probability of each of the scenarios. For some authors, the RCP8.5 scenario is extreme and highly unlikely (van Vuuren, 2011). On the other hand, Christensen et al. (2018) suggest a greater than 35% probability that emissions concentrations will exceed those assumed in RCP 8.5 due to higher uncertainty in per-capita GDP growth rates than in commonly used forecasts. However, as IPCC working group 1 assessment report 6 indicates, for a time horizon up to 2040, the best estimate of the average temperature increase is +1.5°C for all scenarios, except for a slight difference for the worst one (+1.6°C). Thus, the fact that the providers of our two climate risk metrics use different scenarios for a similar horizon should have a limited impact on our results. It is only for more distant horizons that larger discrepancies appear (1.4°C for the most favorable scenario, 4.4°C for the worst scenario, on a horizon of 2081-2100). However, it is unlikely that companies, bankers, and investors will consider such a long time horizon when making decisions about corporate debt. For example, in our sample of bond issues, only 1% of offerings have a maturity of over 40 years.

	comes from the GICS, ICB, and NAICS codes. Then, for each industry-location pair, CRIS assigns subrisk ratings by combining climate projections for the location with sectoral and sovereign vulnerability assessments. The subrisk rating is obtained by computing a weighted arithmetic average of the risk ratings for each industry-location pair, using the geographical and sectoral breakdown as weights. The geographic and sectoral breakdown of the activities is determined using revenues or fixed assets, depending on the sectoral capital intensity.	firm's sites is primarily identified using Bureau van Dijk. Combining sector-specific sensitivities and climate information for the site's location, Four Twenty Seven assigns a rating to each site for each climate hazard. Then, for each climate hazard, the firm-level rating corresponds to the arithmetic average of the site-level ratings. Firm-level climate hazard ratings are then aggregated to form the Operations risk score. Supply chain and market risks depend on industry and country factors.

Spatial resolution	Climate hazards are modeled at the country level, except for 6 countries (Brazil, Canada, China, India, Russia, USA) that are further divided into 4 zones. To assess the exposure of each country/zone to each climate hazard, CRIS relies on quantitative indicators, mostly the percentage of the population, land area, or Gross Domestic Product affected by the climate hazard.	The spatial resolution depends on the hazard[22]:
		• Historical and future floods
		  ○ resolution of 25 x 25 km for rainfall
		  ○ 90 x 90 m for flood frequency and severity
		• Increase in sea levels, 90 x 90 m
		• Historical hurricane and typhoon risks, 25 x 25 km

Time horizons and reference periods	The time horizons are 2050 and 2100 for all subrisks. The reference period is 1961-1990 for all subrisks except increase in storms and increase in sea levels (1985-2015).	• Historical and future floods
		  ○ time horizon: 2030-2040
		  ○ reference period: 1975-2005
		• Increase in sea levels
		  ○ time horizon: 2040
		  ○ reference period: 1986-2005
		• Historical hurricane and typhoon risks
		  ○ time horizon: no projections
		  ○ reference period: 1980-2019

Correlation	The correlation between the CRIS climate risk score and the Four Twenty Seven climate risk score is 62.07%.	

The following table reports the five most-represented SIC2 industries and the five most-represented countries. For each industry and each country, the number in parentheses shows the percentage of observations with this affiliation in the total sample.

	CRIS		Four Twenty Seven	
Rank	Most represented industries (SIC2 industries)	Most represented countries	Most represented industries (SIC2 industries)	Most represented countries
1	28 – Chemical and Allied Products (11.3%)	USA (37.5%)	73 – Business Services (9.2%)	USA (41.0%)
2	73 – Business Services (9.0%)	Japan (22.9%)	49 - Electric, Gas, & Sanitary Services (7.4%)	Japan (24.2%)
3	49 - Electric, Gas, & Sanitary Services (7.7%)	Canada (5.9%)	35- Industrial Machinery & Equipment (6.0%)	Canada (4.8%)
4	35- Industrial Machinery & Equipment (5.5%)	UK (5.5%)	37 – Transportation Equipment (5.8%)	UK (4.8%)
5	37 – Transportation Equipment (5.5%)	France (4.9%)	38 - Instruments & Related Products (5.5%)	France (4.3%)

[22] The Four Twenty Seven measures are therefore more granular than the CRIS measures, but Fiedler et al. (2021) suggest that due to nonlinearities in the climate system, downscaling is unlikely to provide more reliable data for decision-making.

Internet Appendix for

Climate Risk and Capital Structure

Section A of this Internet Appendix discusses the reasons why 2015 is a key year for climate risk awareness. Section B presents additional results that are discussed in the main text.

IA. Section A. Why is 2015 a key year for climate risk awareness?

There are two reasons why 2015 can be considered a breakthrough year for climate risk. On the one hand, the Paris Agreement can be regarded as historic because of the extent of the commitment of countries and financial institutions; on the other hand, it is the launch of a standardization of disclosure of information related to climate risks through the TCFD.

1. COP21, the Paris Agreement

Although the United Nations Framework Convention on Climate Change (UNFCCC), which was adopted in 1992, establishes the general legal framework for international climate change action, it was not until 1997 that countries agreed on quantified emissions limits for developed countries for the first commitment period of the Kyoto Protocol (2008-2012). However, these top-down rules imposed on businesses by governments resulted in little progress in the field of climate change mitigation. In contrast, 2015 was a pivotal year in considering climate change, as economic actors decided to take up the issue. Furthermore, the Paris Agreement, which was signed in December 2015, applies for the first time to all countries, including major developing countries with large emissions, such as India and China.[1] The agreement confirms the objective of keeping global warming below 2°C and calls for continued efforts to limit it to 1.5°C. In advance of the Paris Climate Agreement, several private initiatives involving businesses declared their collective support for an effective climate change agreement to be reached at COP21.[2] One of the core aims of the Paris Agreement is to make all financial flows consistent with a pathway toward low emissions and climate-resilient development. The Agreement sends a signal that all finance, both public and private, needs to be directed toward

[1] On November 4, 2019, the US gave a formal notice of intention to withdraw from the Paris Agreement. The formal departure took effect on November 4, 2020. However, President Joe Biden recommitted the US to the Paris climate accord during his first day in office in January 2021.
[2] For example, CEOs of 79 large firms in 20 economic sectors with operations in over 150 countries and territories signed an open letter in favor of an ambitious deal; see here.

the climate challenge. Several initiatives have since been developed to increase investors' and central banks' awareness of the climate risks to which they are exposed.[3] Between 2013 and 2017, the number of subnational and national-level policy and regulatory measures more than doubled (from 139 to 300),[4] with a substantial rise in system-level initiatives (finance regulations and guidelines and national-level roadmaps for green finance). In 2016, China adopted the "Guidelines for establishing a green financial system". In the same year, the European Union established the High-Level Expert Group on Sustainable Finance (HLEG), which led in 2018 to the European Commission's "Action Plan on Financing Sustainable Growth", including regulations on the establishment of a taxonomy to facilitate green investments not only on disclosures by institutional investors and asset managers but also on carbon-related benchmarks. Furthermore, according to its Climate Change Action Plan 2016-2020, the World Bank pledged to invest $29 billion annually to fight against climate change, where $13 billion comes from the private sector.

2. Climate risks financial disclosures

In April 2015, the G20 Finance Ministers and Central Bank Governors asked the Financial Stability Board (FSB) to review how the financial sector can take account of climate-related issues. Mark Carney, the former chair of the Financial Stability Board (FSB), underlined an urgent need for standard measures and disclosure of climate risks and established an industry-led group, the Task Force on Climate-related Financial Disclosures (TCFD), to design and

[3] For example, the United Nations' Principles for Responsible Investment (PRI) network indicated that in December 2021, $121.3 trillion in assets were under management with 3,826 investors (compared to $21 trillion in assets under management and 203 signatories in 2010). The CDP (carbon disclosure project) had 525 investors for $96 trillion in assets, and climate action 100+ had 360 investors and more than $34 trillion in assets under management (August 2019). The Network of Central Banks and Supervisors for Greening the Financial System (NGFS) was created in 2017 to enhance the role of the financial system to manage risks and to mobilize capital for green and low-carbon investments (108 members and 17 observers as of February 2022).
[4] See UN Environment (2018), "Aligning the financial system with sustainable development". For example, in 2015, Article 173 of France's Law on Energy Transition for Green Growth established new reporting requirements for financial firms to improve the quality of climate disclosure on their investment policy.

deliver these standards. Several initiatives providing information on climate issues already existed (Carbon Disclosure Project, Montreal Carbon Pledge, UN principles for Responsible Investment) but were fragmented and difficult to compare.

The Task Force divided climate-related risks into two categories: risks related to the transition to a lower-carbon economy and risks related to the physical impacts of climate change. Regarding physical climate risks, the framework recommends that organizations describe how resilient their strategies are to scenarios consistent with increased physical climate risks and describe their risk management processes related to the potential financial impacts of, in particular, transport difficulties, supply chain interruptions, damage to property and assets, increased insurance premiums and the potential for reduced availability of insurance on assets in high-risk locations.

The Task Force worked fast and released a preliminary report in March 2016, a draft report in December 2016 and the final report in June 2017. The public consultation received over 300 responses from commenters in 30 countries, and over 100 CEOs publicly supported the Task Force's recommendations (TCFD, 2017), indicating that the TCFD recommendations are largely the result of a collaborative process. Consequently, the TCFD framework has rapidly become the standard for the disclosure of climate risks. In addition, the process of developing the standards itself has led companies to recognize that they will be required to be transparent about climate risk. For example, starting in its 2016 annual report, Aviva, one of the largest insurance companies worldwide, has taken the TCFD framework as the guide for its own climate-related disclosure. In May 2018, ClimateWise's Chairman and Global Chairman of Aon Benfield Dominic Christian underlined that "In creating a universal disclosure framework the ambition of the TCFD is unparalleled and we regard the TCFD as a game-changer for the financial services sector in helping us to communicate our responses to the physical, transition and liability risks of climate change." The European Commission, in its 2018 action plan for a greener economy, stated as a key feature of the plan the revision of "the guidelines on nonfinancial information to further align them with the recommendations of the Financial Stability Board's Task Force on Climate-related Financial Disclosures (TCFD)." In 2021, at least 120 governments, central banks, supervisors, and regulators formally expressed support for the TCFD recommendations (for example, IFRS, European Commission, and Central Bank of Brazil), and more than 2,600 organizations endorsed them (TCFD report 2021). The March 2022 SEC proposal to mandate climate-risk disclosures by US public companies also refers to TCFD guidelines. This rapid standardization of climate risk disclosure has allowed companies to investigate the extent of their own risks, of which they were not always aware, and investors, bankers and insurers to better measure their exposure to these risks.

IA. Section B. Additional results

Figure 1

Long-term debt around the year 2015 for high climate risk and low climate risk firms.

This figure plots the effect of climate risk on leverage over time using the following regression: $BookLev_{it} = \propto + \sum_{t=2011}^{2019} \beta_{1,t} * Climate\ risk_i + \beta_2 * X_{it} + \beta_3 * Z_{it} + \varepsilon_{it}$ where $\beta_{1,t}$ represents the effect of climate risk on leverage over time (with 2010 as the reference year), X_{it} is a vector of control variables (EBIT, Log Age, TobinQ, OpEx, R&DExp, Log TotAssets, PPE, Oil beta, CreditRating), and Z_{it} accounts for firm fixed effects and industry-year fixed effects. Climate risk is a dummy variable equal to one if the firm is a high climate risk firm (>60th percentile within the industry group, using CRIS) and zero if the firm is a low climate risk firm (<40th percentile within the industry group, using CRIS). The regression is conducted on a matched sample, in which each high climate risk firm is matched to a low climate risk firm based on the 2015 value of their book leverage, with a caliper of 0.02. Bands corresponding to 90% confidence intervals based on standard errors clustered by company are included.

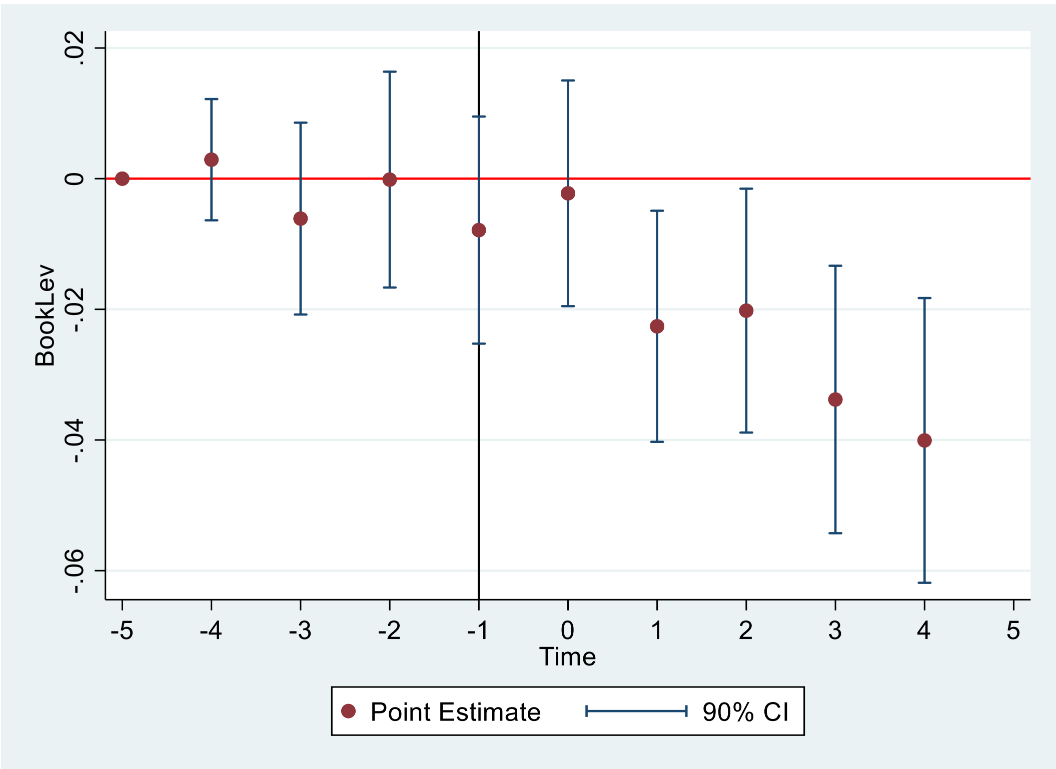

Table IA1

Bank loan, bond loan, and borrower characteristics.

This table reports summary statistics. Descriptive statistics of bank loans, bond loans, and borrower characteristics are reported for the total sample. All Compustat, Thomson-Reuters, Dealscan, and Bloomberg variables are winsorized at the 1st and 99th percentiles, except for CreditRating. The statistics for CreditRating are presented for the firms that are credit rated. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999).

	Bank loan and borrower characteristics			Bond loan and borrower characteristics		
	N	Mean	SD	N	Mean	SD
Climate risk (CRIS)	3,388	32.805	8.933	5,105	34.297	10.826
Climate risk (427)	2,873	40.263	10.295	4,565	41.144	11.729
Spread	3,388	157.882	85.617	5,105	164.264	126.003
Log Amount	3,388	20.620	0.904	5,105	20.231	0.690
Log Maturity	3,388	4.064	0.155	5,105	4.772	0.591
EBIT	3,388	0.091	0.060	5,105	0.090	0.063
Log Age	3,388	3.043	1.220	5,105	3.266	1.112
TobinQ	3,388	1.838	1.020	5,105	1.803	0.949
OpEx	3,388	0.597	0.544	5,105	0.603	0.580
R&DExp	3,388	0.012	0.026	5,105	0.014	0.025
PPE	3,388	0.321	0.268	5,105	0.341	0.267
Log TotAssets	3,388	9.708	1.127	5,105	10.477	1.123
CreditRating	3,007	11.283	2.691	4,789	12.991	2.937

Table IA2

Parallel trend tests.

This table reports the variations in BookLev, EBIT, TobinQ, OpEx, LogTotAssets, and PPE, on matched samples. Each high-risk firm (CRIS rating above the 60th percentile) is matched to a low-risk firm (CRIS rating below the 40th percentile). The matching is conducted using a one-to-one Mahalanobis matching with replacement. In Panel A, the matching is based on the 2015 value of the book leverage, with a caliper of 0.02. In Panels B and C, the matching is based on the 2010, 2013, and 2015 values of BookLev, EBIT, TobinQ, OpEx, Log TotAssets, and PPE. Panels A and C define the 40th and 60th percentiles within each industry group, following the industry groups of Kahle and Walkling (1996). Panel B defines the 40th and 60th percentiles with respect to the total sample. The t-values are rounded to the nearest 0.05. Appendix A presents variable definitions.

Panel A. High and low risk defined within each industry group, matching on the 2015 value of BookLev, caliper 0.02

	Variation from 2013 to 2014				Variation from 2010 to 2014			
	Mean (low risk)	Mean (high risk)	Difference	t_value	Mean (low risk)	Mean (high risk)	Difference	t_value
BookLev	0.007	0.002	0.005	1.2	0.004	-0.004	0.009	1.05
EBIT	-0.002	0	-0.002	-.75	-0.002	-0.009	0.006	1.25
TobinQ	0.019	0.018	0.002	.05	0.309	0.203	0.106	1.05
OpEx	0.005	-0.029	0.034	2.3	0.695	0.58	0.115	2.35
R&DExp	0.001	-0.002	0.003	1.95	-0.004	-0.003	-0.002	-.75
LogTotAssets	0.064	0.042	0.022	1.45	0.316	0.189	0.127	3.95
PPE	-0.003	-0.003	0	-.05	-0.004	-0.015	0.011	1.75

Panel B. High and low risk defined with respect to the total sample, matching on the 2010, 2013, and 2015 values of BookLev, EBIT, TobinQ, OpEx, Log TotAssets, and PPE

	Variation from 2013 to 2014				Variation from 2010 to 2014			
	Mean (low risk)	Mean (high risk)	Difference	t_value	Mean (low risk)	Mean (high risk)	Difference	t_value
BookLev	0.005	0.003	0.002	0.5	0.009	0.005	0.004	0.45
EBIT	-0.003	0.001	-0.004	-1.5	-0.006	-0.007	0.002	0.35
TobinQ	0.037	0.065	-0.028	-0.85	0.305	0.225	0.082	1.25
OpEx	-0.017	-0.026	0.009	1.25	0.584	0.546	0.037	0.95
R&DExp	-0.001	-0.001	0.000	0	-0.001	-0.003	0.002	1.25
LogTotAssets	0.058	0.051	0.006	0.4	0.211	0.207	0.004	0.15
PPE	-0.004	-0.004	0.000	0	-0.009	-0.011	0.002	0.4

Panel C. High and low risk defined within each industry group, matching on the 2010, 2013, and 2015 values of BookLev, EBIT, TobinQ, OpEx, Log TotAssets, and PPE

	Variation from 2013 to 2014				Variation from 2010 to 2014			
	Mean (low risk)	Mean (high risk)	Difference	t_value	Mean (low risk)	Mean (high risk)	Difference	t_value
BookLev	0.002	0.002	0.001	0.1	0.008	-0.001	0.009	1.3
EBIT	-0.001	0	-0.001	-0.45	-0.002	-0.007	0.005	1.2
TobinQ	0.064	0.012	0.051	1.5	0.32	0.222	0.099	1.55
OpEx	-0.012	-0.024	0.012	1.4	0.599	0.595	0.005	0.1
R&DExp	-0.001	-0.002	0.001	0.7	-0.002	-0.003	0.001	0.9
LogTotAssets	0.043	0.045	-0.002	-0.15	0.197	0.191	0.006	0.25
PPE	-0.002	-0.004	0.003	0.7	-0.004	-0.017	0.013	2.35

Table IA3

Climate risk, long-term debt, and firm characteristics after 2015.

This table presents estimates of the effects of overall climate risk on the level of long-term debt after controlling for various firm characteristics after 2015. Panel A reports estimates using the CRIS measure of climate risk. Panel B reports estimates using the Four Twenty Seven measure of climate risk. Column (1) controls for the interaction between Post2015 and EBIT. Column (2) controls for the interaction between Post2015 and TobinQ. Column (3) controls for the interaction between Post2015 and OpEx. Column (4) controls for the interaction between Post2015 and LogTotAssets. Column (5) controls for the interaction between Post2015 and PPE. Column (6) controls for all these interaction terms. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: CRIS climate risk measure

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev
Climate risk*Post2015	-0.00113***	-0.00120***	-0.00136***	-0.00134***	-0.00132***	-0.00117***
	(-4.743)	(-4.824)	(-5.414)	(-5.377)	(-5.167)	(-4.713)
EBIT*Post2015	0.254***					0.246***
	(5.342)					(3.404)
TobinQ*Post2015		0.00869***				0.00246
		(2.919)				(0.599)
OpEx*Post2015			-0.00420			-0.0102**
			(-0.845)			(-1.972)
LogTotAssets*Post2015				-0.00386*		0.000473
				(-1.661)		(0.202)
PPE*Post2015					-0.00520	0.00561
					(-0.474)	(0.505)
Observations	11,367	11,367	11,367	11,367	11,367	11,367
R-squared	0.850	0.849	0.848	0.848	0.848	0.851
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Four Twenty Seven climate risk measure

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev
Climate risk*Post2015	-0.000681***	-0.000750***	-0.000912***	-0.000919***	-0.000882***	-0.000703***
	(-3.418)	(-3.506)	(-4.326)	(-4.350)	(-4.123)	(-3.347)
EBIT*Post2015	0.301***					0.314***
	(5.538)					(3.458)
TobinQ*Post2015		0.00924**				0.00105
		(2.578)				(0.203)
OpEx*Post2015			-0.00153			-0.0103*
			(-0.273)			(-1.738)
LogTotAssets*Post2015				-0.00345		0.00145
				(-1.278)		(0.567)
PPE*Post2015					-0.00973	0.00201
					(-0.815)	(0.171)
Observations	8,933	8,933	8,933	8,933	8,933	8,933
R-squared	0.848	0.845	0.844	0.844	0.844	0.848
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA4

Climate risk and long-term debt: alternative specifications.

This table presents estimates of the effects of climate risk on the level of long-term debt, using alternative specifications. Columns (1) to (5) report estimates using the CRIS measure of physical climate risk. Columns (6) to (10) report estimates using the Four Twenty Seven measure of physical climate risk. Regressions (1) and (6) include country, industry, and year fixed effects. Regressions (2) and (7) include country-year fixed effects. Regressions (3) and (8) include country-year and firm fixed effects. Regressions (4) and (9) include industry-year fixed effects. Regressions (5) and (10) include industry-year and firm fixed effects. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev	(7) BookLev	(8) BookLev	(9) BookLev	(10) BookLev
			CRIS					Four Twenty Seven		
Climate risk	-2.30e-05	-0.00115**		-0.00297***		0.00189***	0.000128		-0.00140***	
	(-0.0382)	(-2.550)		(-5.739)		(3.077)	(0.267)		(-3.175)	
Climate risk*Post2015	-0.00147***	-0.000932***	-0.000852***	-0.00169***	-0.00187***	-0.00101***	-0.000939***	-0.000729**	-0.000731***	-0.000766***
	(-5.899)	(-3.231)	(-3.010)	(-5.023)	(-5.681)					
Observations	11,367	11,367	11,367	11,367	11,367	8,933	8,933	8,933	8,933	8,933
R-squared	0.368	0.299	0.857	0.321	0.860	0.367	0.284	0.856	0.308	0.858
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes			No		Yes			No	
Country-Year Fixed Effects	No	Yes	Yes	No	No	No	Yes	Yes	No	No
Firm Fixed Effects	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Industry Fixed Effects	Yes	No				Yes	No			
Industry-Year Fixed Effects	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Year Fixed Effects	Yes					Yes				

Table IA5

Climate risk and long-term debt: matched samples.

This table presents estimates of the effects of overall climate risk on the level of long-term debt, using matched samples. Each high-risk firm (CRIS rating above the 60th percentile) is matched to a low-risk firm (CRIS rating below the 40th percentile). The matching is conducted using a one-to-one Mahalanobis matching with replacement. Panel A uses a matched sample, in which each high climate risk firm (>60th percentile within the industry group, using CRIS) is matched to a low climate risk firm (<40th percentile within the industry group, using CRIS) based on the 2015 value of the book leverage, with a caliper of 0.02. Panels B and C use a matched sample, in which each high-risk firm is matched to a low-risk firm, using 2010, 2013, and 2015 values of BookLev, EBIT, TobinQ, OpEx, Log TotAssets, and PPE. Panels A and C define the 40th and 60th percentiles within each industry group. Panel B defines the 40th and 60th percentiles with respect to the total sample. Columns (1) and (2) use BookLev as the dependent variable. Columns (3) and (4) use MarketLev as the dependent variable. Columns (1) and (3) report estimates using the CRIS measure of climate risk. Columns (2) and (4) report estimates using the Four Twenty Seven measure of climate risk. Industry groups are defined as in Kahle and Walkling (1996). All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. High and low risk defined within each industry group, matching on the 2015 value of BookLev, caliper 0.02

VARIABLES	(1) BookLev	(2) BookLev	(3) MarketLev	(4) MarketLev
	CRIS	*Four Twenty Seven*	*CRIS*	*Four Twenty Seven*
Climate risk* Post2015	-0.00139***	-0.000812***	-0.000574**	-0.000348
	(-4.340)	(-2.852)	(-2.349)	(-1.498)
Observations	3,945	3,173	3,945	3,173
R-squared	0.866	0.841	0.854	0.852
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Panel B. High and low risk defined with respect to the total sample, matching on 2010, 2013, and 2015 values of BookLev, EBIT, TobinQ, OpEx, Log TotAssets, and PPE

VARIABLES	(1) BookLev	(2) BookLev	(3) MarketLev	(4) MarketLev
	CRIS	*Four Twenty Seven*	*CRIS*	*Four Twenty Seven*
Climate risk* Post2015	-0.00113***	-0.000671***	-0.000472**	-0.000503***
	(-3.973)	(-2.881)	(-2.321)	(-2.607)
Observations	6,268	4,105	6,268	4,105
R-squared	0.852	0.851	0.878	0.883
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Panel C. High and low risk defined within each industry group, matching on 2010, 2013, and 2015 values of BookLev, EBIT, TobinQ, OpEx, Log TotAssets, and PPE

VARIABLES	(1) BookLev	(2) BookLev	(3) MarketLev	(4) MarketLev
	CRIS	*Four Twenty Seven*	*CRIS*	*Four Twenty Seven*
Climate risk*Post2015	-0.00105***	-0.000716***	-0.000488**	-0.000447**
	(-3.854)	(-2.815)	(-2.371)	(-2.200)
Observations	6,260	4,090	6,260	4,090
R-squared	0.887	0.881	0.887	0.887
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table IA6

Climate risk and long-term debt: quantile regressions.

This table presents estimates of the effects of climate risk on the level of long-term debt, using quantile regressions. Columns (1) to (4) report estimates using the CRIS measure of physical climate risk. Columns (5) to (8) report estimates using the Four Twenty Seven measure of physical climate risk. Regressions (1) and (5) report the quantile regression at the 20th percentile. Regressions (2) and (6) report the quantile regression at the 40th percentile. Regressions (3) and (7) report the quantile regression at the 60th percentile. Regressions (4) and (8) report the quantile regression at the 80th percentile. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev	(7) BookLev	(8) BookLev
	CRIS - 20th percentile	*CRIS - 40th percentile*	*CRIS - 60th percentile*	*CRIS - 80th percentile*	*Four Twenty Seven - 20th percentile*	*Four Twenty Seven - 40th percentile*	*Four Twenty Seven - 60th percentile*	*Four Twenty Seven - 80th percentile*
Climate risk*Post2015	-0.000355*** (-2.771)	-0.000473*** (-3.268)	-0.000628*** (-3.705)	-0.000690*** (-3.762)	-0.000337*** (-3.094)	-0.000399*** (-2.969)	-0.000481*** (-4.010)	-0.000520*** (-4.078)
Observations	11,367	11,367	11,367	11,367	8,933	8,933	8,933	8,933
R-squared	0.770	0.821	0.821	0.790	0.767	0.819	0.819	0.786
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA7

Climate subrisks and long-term debt.

This table presents estimates of the effects of climate subrisks on the level of long-term debt using BookLev as the dependent variable. Panel A reports estimates using the CRIS measures of climate subrisks. Panel B reports estimates using the Four Twenty Seven measures of climate subrisks. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: CRIS climate risk measure

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev	(7) BookLev
Droughts*Post2015	-0.00136*** (-5.142)						
Heat waves*Post2015		-0.000861*** (-3.304)					
Storms*Post2015			-0.000915*** (-5.184)				
Heavy rainfall*Post2015				-0.000968*** (-5.801)			
Temperature rise*Post2015					-0.000160 (-0.500)		
Rainfall patterns*Post2015						-0.000683* (-1.761)	
Sea level rise*Post2015							-0.000838*** (-4.040)
Observations	11,367	11,367	11,367	11,367	11,367	11,367	11,367
R-squared	0.848	0.847	0.848	0.848	0.846	0.846	0.847
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Four Twenty Seven climate risk measure

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev
OperationsRiskScore*Post2015	-0.00120*** (-4.736)			
Floods*Post2015		-0.00199*** (-5.985)		
Sea level rise*Post2015			-0.00105*** (-3.414)	
HurricanesTyphoons*Post2015				-0.000561*** (-5.002)
Observations	8,933	8,933	8,933	8,933
R-squared	0.844	0.845	0.843	0.844
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table IA8

Climate risk and long-term debt, alternative horizons and scenarios.

This table presents estimates of the effects of climate risk on the level of long-term debt using alternative horizons and scenarios. Columns (1) and (3) report estimates using the CRIS low emission scenario measure of climate risk. Columns (2) and (5) report estimates using the CRIS high emission scenario measure of climate risk. Column (4) report estimates using the CRIS medium emission scenario measure of climate risk. Regressions (1) and (2) report estimates using the 2050 horizon measure of climate risk. Regressions (3), (4), and (5) report estimates using the 2100 horizon measure of climate risk. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev
Climate risk measure	Low-emission scenario, 2050 horizon	High-emission scenario, 2050 horizon	Low-emission scenario, 2100 horizon	Medium-emission scenario, 2100 horizon	High-emission scenario, 2100 horizon
Climate risk*Post2015	-0.00135***	-0.00132***	-0.00105***	-0.000943***	-0.000856***
	(-5.204)	(-5.271)	(-4.508)	(-4.171)	(-3.955)
Observations	11,357	11,357	11,357	11,357	11,357
R-squared	0.848	0.848	0.848	0.847	0.847
Constant	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table IA9

Climate subrisks and long-term debt, alternative horizons and scenarios.

This table presents estimates of the effects of climate subrisks on the level of long-term debt using alternative horizons and scenarios. The effect of each subrisk is estimated with a separate regression on the total sample, comprising 11,367 firm-year observations. Columns (1) and (3) report estimates using the CRIS low emission scenario measure of climate risk. Columns (2) and (5) report estimates using the CRIS high emission scenario measure of climate risk. Column (4) report estimates using the CRIS medium emission scenario measure of climate risk. Regressions (1) and (2) report estimates using the 2050 horizon measure of climate risk. Regressions (3), (4), and (5) report estimates using the 2100 horizon measure of climate risk. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev
Climate risk measure	Low-emission scenario, 2050 horizon	High-emission scenario, 2050 horizon	Low-emission scenario, 2100 horizon	Medium-emission scenario, 2100 horizon	High-emission scenario, 2100 horizon
Droughts*Post2015	-0.00141***	-0.00138***	-0.00137***	-0.00128***	-0.00120***
	(-5.133)	(-5.220)	(-5.155)	(-5.200)	(-5.373)
Heat waves*Post2015	-0.00114***	-0.000944***	-0.000970***	-0.000664***	-0.000529**
	(-4.352)	(-3.530)	(-3.747)	(-2.805)	(-2.419)
Storms*Post2015	-0.000915***	-0.000915***	-0.000677***	-0.000677***	-0.000677***
	(-5.184)	(-5.184)	(-4.247)	(-4.247)	(-4.247)
Heavy rainfall*Post2015	-0.00100***	-0.00101***	-0.000951***	-0.000792***	-0.000777***
	(-5.093)	(-5.848)	(-4.901)	(-4.116)	(-4.026)
Temperature rise*Post2015	-0.000195	-0.000320	-0.000299	-0.000309	-0.000256
	(-0.647)	(-1.159)	(-1.109)	(-1.248)	(-1.343)
Rainfall patterns*Post2015	-0.000956***	-0.000747**	-0.000804**	-0.000787**	-0.000618**
	(-2.601)	(-2.064)	(-2.279)	(-2.337)	(-2.327)
Sea level rise*Post2015	-0.000838***	-0.000764***	-0.000545***	-0.000545***	-0.000465***
	(-4.040)	(-3.821)	(-3.245)	(-3.245)	(-2.962)

Table IA10

Credit rating and climate risk, alternative horizons and scenarios.

This table presents estimates of the effects of overall climate risk on credit rating, using alternative horizons and scenarios. The regressions use CreditRating as the dependent variable for firm-year observations with a credit rating. Columns (1), (2), (5), and (6) report estimates using the CRIS low emission scenario measure of climate risk. Columns (3), (4), (9), and (10) report estimates using the CRIS high emission scenario measure of climate risk. Columns (7) and (8) report estimates using the CRIS medium emission scenario measure of climate risk. Regressions (1) to (4) report estimates using the 2050 horizon measure of climate risk. Regressions (5) to (10) report estimates using the 2100 horizon measure of climate risk. Regressions (1), (3), (5), (7), and (9) include country-industry and year fixed effects. Regressions (2), (4), (6), (8), and (10) include firm and year fixed effects. All regressions exclude observations with missing Log IntCoverage. All regressions include a constant and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, Log IntCoverage, and WorkingCap. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) CreditRating	(2) CreditRating	(3) CreditRating	(4) CreditRating	(5) CreditRating	(6) CreditRating	(7) CreditRating	(8) CreditRating	(9) CreditRating	(10) CreditRating
Climate risk measure	Low-emission scenario, 2050 horizon		High-emission scenario, 2050 horizon		Low-emission scenario, 2100 horizon		Medium-emission scenario, 2100 horizon		High-emission scenario, 2100 horizon	
Climate risk	0.00786		0.00745		0.000269		-0.00327		-0.00260	
	(0.607)		(0.602)		(0.0260)		(-0.335)		(-0.286)	
Climate risk*Post2015	0.00404	-0.00206	0.00403	-0.00200	0.00527	-0.000543	0.00538	-8.92e-05	0.00471	-0.000273
	(0.843)	(-0.498)	(0.868)	(-0.504)	(1.234)	(-0.146)	(1.280)	(-0.0247)	(1.166)	(-0.0784)
Observations	7,602	7,602	7,602	7,602	7,602	7,602	7,602	7,602	7,602	7,602
R-squared	0.556	0.915	0.556	0.915	0.556	0.915	0.556	0.915	0.556	0.915
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry Fixed Effects	Yes		Yes		Yes		Yes		Yes	
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA11

Climate risk and long-term debt: exclusion of polluting industries.

This table presents OLS estimates of the effects of overall climate risk on the level of long-term debt using BookLev as the dependent variable, after exclusion of the most polluting industries. Columns (1) and (3) report estimates using the CRIS measure of climate risk. Columns (2) and (4) report estimates using the Four Twenty Seven measure of climate risk. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev
Climate risk measure	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven
Sample	Excluding Top5 polluting industries	Excluding Top5 polluting industries	Excluding Top10 polluting industries	Excluding Top10 polluting industries
Climate risk*Post2015	-0.00123***	-0.000822***	-0.00121***	-0.000861***
	(-4.656)	(-3.533)	(-4.505)	(-3.602)
Observations	10,002	7,915	9,182	7,261
R-squared	0.835	0.832	0.838	0.835
Constant	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table IA12

Climate risk and long-term debt: regressions by industry groupings.

This table presents OLS estimates of the effects of overall climate risk on the level of long-term debt using BookLev as the dependent variable, for different industry groupings. Columns (1), (3), (5), and (7) report estimates using the CRIS measure of climate risk. Columns (2), (4), (6), and (8) report estimates using the Four Twenty Seven measure of climate risk. Regressions (1) and (2) report estimates using observations in manufacturing (SIC 2000-3999). Regressions (3) and (4) report estimates using observations in transportation, communication, electric, gas, and sanitary services (SIC 4000-4999). Regressions (5) and (6) report estimates using observations in wholesale trade and retail trade (SIC 5000-5999). Regressions (7) and (8) report estimates using observations in services (SIC 7000-8999). All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) BookLev	(2) BookLev	(3) BookLev	(4) BookLev	(5) BookLev	(6) BookLev	(7) BookLev	(8) BookLev
	SIC20-39		SIC40-49		SIC50-59		SIC70-89	
Climate risk measure	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven	CRIS	Four Twenty Seven
Climate risk*Post2015	-0.00167***	-0.000955***	-0.00185***	-0.000540	-0.00174**	-0.00214***	-0.00192**	-0.000863*
	(-4.391)	(-2.660)	(-3.447)	(-1.399)	(-2.022)	(-2.750)	(-2.434)	(-1.762)
Observations	5,461	4,423	2,018	1,499	1,280	958	1,548	1,210
R-squared	0.791	0.779	0.879	0.866	0.881	0.881	0.854	0.875
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA13

Physical climate risk, long-term debt, and regulatory risk.

This table presents estimates of the effects of physical climate risk on the level of long-term debt, after controlling for regulatory risk. Columns (1) and (2) report estimates using the CRIS measure of physical climate risk. Columns (3) and (4) report estimates using the Four Twenty Seven measure of physical climate risk. Columns (5) and (6) report estimates using the Sautner et al. (2020) measure of physical climate risk. All regressions control for regulatory risk using the Sautner et al. (2020) measure of regulatory risk. Regressions (2), (4), and (6) control for the interaction between Post2015 and Regulatory risk. All regressions include a constant, firm and year fixed effects, and control for EBIT, Log Age, TobinQ, OpEx, R&DExp, LogTotAssets, PPE, Oil beta, and CreditRating. Appendix A presents variable definitions. The sample comprises all firms in the MSCI World index from 2010 to 2019, excluding financial firms (SIC 6000-6999). Standard errors are clustered at the firm level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	BookLev	BookLev	BookLev	BookLev	BookLev	BookLev
	CRIS		Four Twenty Seven		Sautner et al. (2020)	
Climate risk					0.0134	0.00948
					(0.921)	(0.654)
Climate risk*Post2015	-0.00111***	-0.00105***	-0.000628**	-0.000590**	-0.0599**	-0.0551**
	(-3.520)	(-3.311)	(-2.230)	(-2.087)	(-2.490)	(-2.295)
Regulatory risk	0.00192	0.00852*	0.00193	0.00868*	0.00151	0.00990**
	(0.529)	(1.877)	(0.485)	(1.680)	(0.408)	(2.073)
Regulatory risk*Post2015		-0.0134**		-0.0135**		-0.0169***
		(-2.201)		(-1.985)		(-2.659)
Observations	8,762	8,762	6,994	6,994	8,762	8,762
R-squared	0.842	0.842	0.841	0.841	0.841	0.841
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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