Global Climate Risk, Cost of Debt, and Analyst Forecast

By

Qixin Liu

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Department of Business Administration

I.H. Asper School of Business

University of Manitoba

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Abstract

This research examines the impact of climate risk on firm financing related factors-cost of debt and analyst forecast -from a cross-country empirical perspective. The increasing influence of climate risk on economy and firm performance is realized by all market participants and triggers deeper concern on firm financing activities in high-climate-risk countries. In this paper, we propose that climate risk is positively associated with cost of debt. We believe the increased default risk and an unbalanced demand-supply relationship between investors and borrowers lead to the increase of cost of debt under high climate risk. Moreover, we investigate the moderating role of forecast accuracy and analysts following in the relationship between climate risk and cost of debt. We think that when firms have more accurate forecasts and more analysts following, their cost of debt will increase less under the same climate risk level. Empirically, We conduct mixed-effects models to tests the above proposition with a sample from 33 countries from the year 2004 to 2018. Our results show a nonsignificant relationship between climate risk and cost of debt and show significant negative moderating effects of forecast accuracy and analysts following on the relationship between climate risk and cost of debt.

Keywords: climate risk, cost of debt, forecast accuracy, analysts following

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Table of Contents

List of Tables

Global Climate Risk, Cost of Debt, and Analyst Forecast

1. Introduction

The world average temperature was 1.14 degrees Celsius higher compared to the late 19th century. Since 2014, there are six most warming years took place. 2016 is the warmest year on record[1] and 2019 is the second[2]. All the numbers imply that the increasing extreme events are caused by climate change. In addition, damages caused by adverse climate phenomenon to society and economy are severe. In 2019, there are 14 disasters that cost more than a dozen billion dollars in U. S. alone[3]. Therefore, research about climate change starts to become popular nowadays. Not only in climate-sensitive fields like agriculture but also in psychology, sociology, and economics. For example, Cologna and Siegrist (2020) study how the role of trust towards scientists affects their behavior of mitigating and adapting climate change; Lee, Min and Yook (2015) find carbon emissions persistently decrease firm value; Dell, Jones and Olken (2009) study the relationship between temperature and economic output, and find a negative relationship based on US data.

Studies about the impact of climate risk on economy are well established and recognized (e.g., Barreto, Makihira & Riahi,2003; Bosello, Roson & Tol, 2006; Wennersten, Sun & Li, 2015). Previous studies are trying to illustrate this topic in a specific country or region. For instance, Alam et al., (2011) provide a political economic plan under climate change in Bangladesh; Nordhaus (2006) finds the difference of per capital income between Africa and other countries with higher wealth can be explained by climate factors. To extend this topic geographically, we include country-level climate risk data as a predictor in this study. This data is published on Germanwatch and contains annual Global Climate Risk Index (CRI) from 2004 to 2018 which measures the loss due to extreme weather events like storms, drought, floods, etc. Previous studies also trying to interpret the relationship between climate risk and firm performance. Barrot and Sauvagnat (2016) find firm's stock process and sales growth are decreased when one of their largest suppliers suffers from extreme climate events; Brown et al., (2017) research on the use of credit under extreme temperature and find extreme cold condition corresponds to a cash flow shock to firms; Kim et al., (2015) investigate the relationship between

[1] https://climate.nasa.gov/evidence/
[2] https://www.noaa.gov/climate
[3] https://www.climate.gov/news-features/blogs/beyond-data/2010-2019-landmark-decade-us-billion-dollar-weather-and-climate

carbon risk and cost of equity capital and find management of carbon emission can mitigate the positive effect of carbon risk on cost of equity capital.

In this study, we also study the relationship between climate risk and firm performance. However, instead of focusing firm's operating performance, we plan to study it through the firm's financing performance. Recently, not only firms but also investors in markets are aware of the increasing influence of climate change on economics. Bansal and Ochoa (2012) suggest that high temperature damages firms' return of equity. Whereas the market of real estate becomes depressed under high sea level rise (Bernstein et al., 2019). Some researchers also investigate the relationship between weather, firm economics and investors' attention and ability to climate changes (Pankratz et al., 2019). They suggest that analysts and investors not take all the information about extreme climate change into account when making decisions thus tend to have a decreased return during their investments. However, how the analysts and investors making decisions with different climate risk information differently and how those decisions influence firms' financing performance under different climate risks are not well addressed. Therefore, to further research the influence of climate risk on firm financing activities, we investigate the impact of climate risk on firm financing related factors-cost of debt and analyst forecast-from a cross-country empirical perspective in this paper. We first research the impact of country-level climate risk on cost of debt, and then include analyst forecast factors as moderators to further study how firm financing activities is influenced by climate risk. Lastly, except external factors analyst forecast, we also include one more external factor (country-level governance environments) and one internal factor (firm-level earnings skewness)

Our study contributions to firm financing literature by including cost of debt and analyst forecast factors. First, it extends the research of climate risk and cost of debt by adding analyst forecast related factors. Studies investigate the relationship between climate change and cost of debt is abundant. Jung et al., (2018) find a positive association between cost of debt and country-level carbon emission when firms did not respond to certain carbon disclosure regulations. Kling et al., (2018) also find social and physical investment can weaken the association between cost of debt and climate risk. However, in our study, we will introduce analyst forecast related factors to enrich the impact of climate risk on cost of debt. Second, it expands firm financing research by exploring the moderating effect of analyst forecast accuracy and analysts following on the relationship between climate risk and cost of debt. Previous studies show the regulation or financial disclosures have a relationship with analyst forecast (Lang & Lundholm, 1996; Irani & Karamanou, 2003; Bailey et al, 2003; Bernardi & Stark, 2018). However, Dhaliwal et al., (2012) and Vanstraelen (2003) suggest nonfinancial disclosures could also impact analyst forecast behavior. Complementing their research on non-financial information, our study examines whether country-level climate risk is related to analyst forecast accuracy and the number of analysts following. In addition, we examine how the behavior of analysts under different climate risk levels will further impact firms' internal financing indicator-cost if debt.

The remainder of this study is structured as follows: in section 2, a literature review is provided for our main constructs. One direct hypothesis and four moderating hypothesis will be developed based on it. In the third section, a detailed sample selection and empirical models are described, and then, a multilevel empirical analysis will be conducted using mixed-effects model to examine the research questions. Section four reveals the empirical results, discusses its implications based on the results, and provides several additional analyses for robustness. Finally, a discussion of the result and conclusion will be showed including the limitations and suggested future research directions.

2. Literature Review and Hypothesis Development

2.1 Climate Risk and Cost of Debt

We first investigate the relationship between climate risk and cost of debt. Extreme climate change could cause potential massive losses and lead to high financial and credit risks (Ginglinger & Moreau, 2019). Climate risk is a material external factor that influences firm earnings and cash volatility (Dichev & Tang, 2009). With an uncertain firm performance, the risks of a firm to profit, operation and liquidity are raised, and the default risk is also increased. From a risk awareness perspective, the default risk is an indicator of investment activities and financing activities for lenders and borrowers (He & Hu, 2016). On one hand, lenders or investors who are aware of the increasing climate risk will request compensation for the risk that the borrowers may not be able to repay their funds and therefore increasing cost of debt for borrowers from high-climate-risk areas. On the other hand, borrowers or shareholders tend to take wealth from firm assets that belong to investors or take risk-seeking projects to transfer the risk from themselves to investors when facing distresses such as extreme climate events (He & Hu, 2016). Those risk-seeking decisions will eventually damage the benefits of investors and cause an increase of cost of debt.

From a risk hedging perspective, firms experiencing high climate risk need to apply adaptive strategies to mitigate external uncertainty. For example, some firms use strategies like controlling emissions and producing green products that facilitate the resource and capability of firms' adaptation management (Kolk & Pinkse, 2004; 2005). Studies also show that firms with high climate risk will have more long-term debt than short-term debt and hold more cash for hedging (Itzkowitz, 2013; Huang et al., 2018). To conduct those strategies, firms will have a large demand for funds and resources. On the contrary, the supply of funds to high climate risk firms will decrease because of the higher default risk. This unbalanced demand-supply relationship will cause an increase of cost of debt for high climate risk firms. Based on previous perspectives, we hypothesis:

H1: Climate risk is positively associated with cost of debt.

2.2 Analyst Forecast

The role of analyst forecast in reducing information asymmetry is well known (Mansi, Maxwell & Miller, 2011; Barth & Hutton, 2000; Abarbanell & Bernard, 1992). The information of analysts' targeted firms will spread through their forecast reports to all market participants. As global climate risk becomes a popular issue in society, market participants tend to take it into consideration when making decisions (Mansley & Dlugolecki, 2001). The need for analyst forecasts is increasing so that they can obtain more information and recommendations of those firms in high-climate-risk countries. Some participants are even willing to pay for those forecast reports (Kirk, 2011). Therefore, we think global climate risk can have an impact on analyst forecast behaviors. On one hand, firms in high-climate-risk countries call more attention from analysts due to the increasing demand for forecast reports from bankers, investors, managers, etc. the number of analysts following those firms will also raise (Bhushan, 1989). What's more, analysts may tend to make more effort when analyzing those firms to fulfill their customers' lack of information. In this case, they need to estimate whether those firms have the ability to hedge climate risk and make the movement to adapting changes from external environment. With a better understanding of the capability and situation of high-climate-risk firms, their recommendations and forecasts will become more comprehensive and accurate[5].

[5] One study also holds an opposite point that climate change reduces analyst forecast accuracy because analysts underestimate the sensitivity of firms on climate change or incorrectly estimate information on climate risk. (Pankratz et al., 2019); Moreover, Hope and Kang (2005), external country-level risk could decrease analysts forecast accuracy by triggering a more volatile country-wide operating environment. Riahi-Belkaoui and Alvertos

On the other hand, climate changes as a risk that is hard to predict are causing extra uncertainty for firms. Whereas analysts have a strong tendency of herding under uncertain circumstances (Lin, 2018; Moses, 1991) or with high task difficulty (Kim & Pantzalis, 2003). This means their forecast may align with their peers' forecasts for firms in high-climate-risk countries. Thus, the volatility of forecast values towards those firms is narrow down. Instead of making a bold forecast to make their report stand out, they rather have a conservative argument to prevent reputation damage. However, when analyzing firms in low-climate-risk countries, their forecasts value could have a high range. In other words, the average error of all the analyst forecasts is larger if the majority of analysts making high-volatility forecast values to firms in low-climate-risk countries while making consensus forecasts values to firms in high-climate-risk countries. In conclusion, we think climate risk can impact analyst forecasts by increasing the accuracy of forecasts and the number of analysts following one firm.

2.3 The Moderating Role of Analyst Forecast

When talking about analyst forecasts, previous researchers primarily examine the role of analysts in the cost of equity. Botosan (1997) suggests there is a negative association between corporate disclosure and cost of equity when the number of analysts following is low; He et al., (2013) and Gebhardt, Lee, and Swaminathan (2001) state that the dispersion of analysts earning forecast can enhance the ex-ante cost of equity capital but decrease firm's implied cost of capital. Instead of cost of equity, we study how analyst forecast can affect cost of debt in this paper. First, the ability of analysts to reduce information asymmetry is well researched. Piostroski and Roulstone (2004) state that analysts obtain information about stock price from all firms' news events and spread them during making forecast. In addition, Ramnath (2002) finds analysts using one firms' information to alter their forecast of other firms in the same industry. Because of the reduction of information asymmetry, investors will have more references such as climate risk related information to estimate the future return and value of firms. As investors have a more accurate estimation of firm value, the possibility of default will also decline and therefore, reduce cost of debt even under high climate risk.

Second, studies indicate information obtained from analysts can be a monitor of managers' behavior (Moyer et al., 1989; Defond & Hung, 2007; Chakravarty & Grewal, 2016).

(1998) also find a positive relationship between country risk and forecast accuracy and a negative relationship between country return and forecast accuracy.

The information produced by analyst forecasts can become a market discipline that measures the decision-making of managers. In this way, analyst forecast can become a monitoring mechanism that could reduce the cost of control and then reduce cost of debt. In addition, the monitoring role of analyst forecast can also prevent managers from making risk-seeking decisions when hedging climate risk. In conclusion, with more analysts following and more accurate of their forecasts, market participants can mitigate information asymmetry and supervise firm operations. Therefore, we propose:

H2a: Forecast accuracy weaken the association between climate risk and cost of debt.

H2b: Analysts following weaken the association between climate risk and cost of debt.

2.4 The Moderating Effect of Firm-level Earnings Skewness and Country-level Governance Environments

To further investigate the effect of country-level climate risk on cost of debt from other perspectives, we introduce two more moderators from firm-level and country-level separately. From an internal context, we use earnings skewness to represent the stability of earnings and then examine how earnings stability could affect the relationship between climate risk and cost of debt. Study shows that resilience or adaptation towards risk tends to be enhanced under uncertainty (Berkes, 2007). For firms that have stable earnings, their ability to hedging risk may be insufficient. This will lead to a fluctuation of their performance under high climate risk and then increase the cost of debt by increasing investors; default risk as discussed above. Therefore, we propose that the positive relationship of climate risk and cost of debt tend to mitigate when the stability of earning is low which means earnings skewness is high.

H3a: Earnings skewness weaken the association between climate risk and cost of debt.

Except for analyst forecast, another factor from external environment is governance environment, we introduce it to capture the quality of a country's governance. Except for the influence of climate risk, studies indicate that the country-level governance environment has a significant impact on firm performance (Yasar, Paul & Ward, 2011; Daske, Haul, Leuz & Verdi, 2008). Here, we use measures of country-level legal system and property rights to imply the quality of country governance environment (Bradshaw et al., 2019). Property rights protected by country legal system are shown a significant positive effect on firm performance (Acemoglu, Johnson & Robinson, 2002). Also, studies imply that country's regulatory environment has an impact on the behaviors of bankers, investors and analysts (Haselmann & Wachtel, 2010;

Bottazzi et al., 2009; Barniv et al., 2005). A high-quality governance environment means it can protect investors' interests and enforce those laws with certain guarantees so that enhance the possibility of investors receiving their funds. Thus, countries with a high-quality governance environment could attract more investors by mitigating partial risks due to climate change. Those countries also can offer better legal support when firms applying adaptive strategies. Thus, we propose:

H3b: High-quality governance environment weaken the association between climate risk and cost of debt.

3. Methodology

3.1 Data

We retrieved data as following: (1) independent variable: *climate risk (ACRI)* is from Germanwatch, we obtain Global Climate Risk Index (CRI) from 2004 to 2018 regarding Huang et al., (2018) which measures the economic loss caused by extreme weather events such as storms, floods, drought, etc. Our study includes both long-term CRI score (13-year window) from 1986-2018 and annual CRI score for the years 2004 to 2018. Also, we use ACRI which is the negative value of CRI score in the report to make higher climate risk represent higher ACRI value. (2) dependent variable: *cost of debt (COD)* is captured from DealScan, which contains detailed loan-related information internationally. The loan data are compiled for each deal and facility and applies an all-in-drawn approach to measure cost of debt which is calculating as the annual premium paid over LIBOR (Ivashina, 2005). We merge DealScan with Compustat following the method of Chava and Roberts (2008). (3) moderators: *forecast accuracy (FAccuracy)* is calculated using data from IBES to present an inverse measure of forecast error. Following the measurement from Dhaliwal et al., (2012), forecast error is defined as the average of the absolute errors of all forecasts made in the year for target earnings, scaled by the stock price at the beginning of the year:

$$FAccuracy = -forecast\ error_{j,t} = -\frac{1}{N}\sum_{k=1}^{N}\frac{\left|FEPS_{j,t} - AEPS_{j,t}\right|}{P_{j,t}} \tag{1}$$

where subscripts j, and t denote firm j, year t, FEPS is the forecast earnings per share and AEPS is the actual earnings per share. We also retrieve data of analysts following (*NAnalysts)* from IBES which is measured by the log number of analysts following one firm; financial and accounting information are downloaded from Compustat North America and global databases. And we obtain firm-level earnings skewness (*Skewness*) following the study of Bhattacharya et al., (2003) to address our firm-level moderating analysis. It is measured by the mean–median difference of EPS deflated by the stock price or skewness coefficient. (5) To examine country-level moderating effect, we describe the proxy of legal environment using Worldwide Governance Indicators (WGI) following Ding et al., (2021). WGI captures the quality of Country-level legal and business environments. It is measured as the sum of total score from two dimensions of country-level governance. These two dimensions are political stability and government effectiveness. All the variables included are described in Appendix A.

We control for both firm-level and country-level factors. At the firm-level, we include the number of loans related and analyst forecast related variables to control other factors that may confound the relationship between CRI, cost of debt and forecast accuracy. For cost of debt related factors, we also include loan maturity (*LMaturity*), loan size (*LSize*), and the number of lenders (*NLenders*) following Kim et al., (2011). Based on the measurement from Dhaliwal et al., (2012), forecast horizon (*FHorizon*) is defined as the number of days between earnings announcement date and forecast date which is controlled because it may affect how much information analysts can obtain and therefore affect forecast accuracy. Also, we control for the number of estimations (*NEstimation*) because the more estimations of one firm are made, the more competitive among all the analysts and then motivate them to make accurate forecasts. The measurements of all control variables are present in Table 1.

We further control for firm *Leverage* (measured using long-term debt divided by total assets at year-end) to serve as a proxy for the probability of default and control for market to book ratio, and dividend. We also include *Size*, *PPE*, *ROA* which represent firm size (The natural log of total assets at year-end), firm tangibility (Net property, plant and equipment divided by total assets at year-end) and return on asset (Earnings before extraordinary item divided by average total assets at year-end), respectively. Moreover, Hope (2003) indicates negative earnings cause a more conservative accounting system and fluctuated performance thus make firms difficult to predict. To control for this effect, we include *Loss* that equals 1 if the firm reports negative earnings in the year, and 0 otherwise. Finally, at country-level, we control for GDP per capita as a proxy for economic development. All of the aforementioned continuous firm-level variables are winsorized at the 7.5% and 92.5% levels to eliminating outliers. Then, we exclude data from firms in financial sector and regulated sector and eliminated countries with less than 50 observations based on Kim, Kim and Zhou (2017). After emerging data from IBES, DealScan, Compustat, and Germanwatch, our sample has 14,046 deal-firm-year observations in 33 countries from the years 2004 to 2018.

3.2 Empirical Model

As a cross-country analysis, our sample contains multiple levels of observations. Thus, we apply a multilevel mixed-effects model to estimate our sample to avoid the bias of interdependency within each level. The Mixed-effects model also known as multilevel models and hierarchical models and it contains both fixed effects and random effects to better interpret the data. It also can capture data structure by deal, firm and country level, therefore, presenting the most reasonable structure with the best goodness-of-fit (Liu et al., 2016). For H1, a three-level mixed model is applied from deal, firm and country levels, respectively. Equation (2) illustrates cost of debt for deal i , firm j in year t:

$$COD_{i,j,t} = \beta_0 + \beta_1 ACRI_t + \sum_k Control_{j,t} + \varepsilon_{i,j,t} \tag{2}$$

As mentioned in section 2.2, we proposed an impact of climate risk on analyst forecast accuracy and analysts following. To avoid the bias caused by endogeneity, we test the relationship between climate risk, forecast accuracy and analysts following before we examine H2a and H2b. Our sample for this test contains 40,043 data from 41 countries, and the model we apply is shown in Equation (3). A two-level mixed model is applied from firm, country levels to illustrate analyst forecast for firm j in year t:

$$FAccuracy_{j,t}/NAnalysts_{j,t} = \beta_0 + \beta_1 ACRI_t + \sum_k Control_{j,t} + \varepsilon_{j,t} \tag{3}$$

Then, following the two-stage least square regression approach, we use the fitted value of forecast accuracy from Equation (3) as a moderator of the relationship between climate risk and cost of debt to test H2a. the model is showed as Equation (4) which could solve the correlation between climate risk and analyst forecast factors.

$$COD_{i,j,t} = \beta_0 + \beta_1 ACRI_t + \beta_2 FAc\widehat{cura}cy_{j,t} + \beta_3 ACRI_t * FAc\widehat{cura}cy_{j,t} + \sum_k Control_{j,t} + \varepsilon_{j,t} \tag{4}$$

As above, to test H2b, we use Equation (5).

$$COD_{i,j,t} = \beta_0 + \beta_1 ACRI_t + \beta_2 NAn\widehat{alys}ts_{j,t} + \beta_3 ACRI_t * NAn\widehat{alys}ts_{j,t} + \sum_k Control_{j,t} + \varepsilon_{j,t} \tag{5}$$

4. Empirical Results

4.1 Univariate Analysis

Table 1 shows the descriptive statistics for our sample for testing the relationship between climate risk, cost of debt and analyst forecast. This sample contains 14,046 deal-firm-year observations in 33 countries from the years 2004 to 2018. The mean and median annual ACRI are 0.734 and 0.654, respectively. Firms in our sample have a median ROE of 0.076, ROA of 0.031, market-to-book ratio of 2.922, coverage ratio of 0.278 and the natural log of their assets (Size) is 7.868, The median value of the log of a country's per capita GDP (LGDP) is 10.785, the median value of GDP Growth is 2.129 percent. The median number of fitted forecast accuracy and analysts following are -0.026 and 1.905, respectively. Besides the variables lists above, we include other variables related to cost of debt. The median of loan maturity and loan size are 57.212 days and $1138.877, the medians number of lenders is 8.735.

Table 1 Descriptive Statistics

The sample of climate risk, cost of debt and fitted value of analyst forecast

Variables	Observations	Mean	Std. Dev.	min	max	25%	Median	75%
COD	14045	5.2	.577	4.094	6.109	4.828	5.193	5.617
ACRI	14046	.734	.588	-3.205	1.587	.634	.654	1.125
$\widehat{\text{FAccuracy}}$	14046	-.026	.02	-.113	.028	-.038	-.023	-.011
$\widehat{\text{NAnalysts}}$	14046	1.905	.649	-1.073	3.105	1.528	2.039	2.452
LSize	14046	1138.877	2363.072	.597	61000	200	500	1225
LMaturity	13966	57.212	20.529	1	324	48	60	60
NLenders	14028	8.735	7.207	1	113	4	7	12
Senior	14046	.999	.037	0	1	1	1	1
Size	14046	7.868	1.384	3.383	9.649	6.837	7.935	9.115
Leverage	14046	.278	.158	0	.515	.158	.274	.407
PPE	14046	.313	.256	.018	.803	.097	.223	.513
ROA	14046	.031	.084	-.538	.139	.012	.041	.074
MTB	14046	2.922	2.187	.394	8.373	1.392	2.226	3.753
Loss	14046	.192	.394	0	1	0	0	0
ROE	14046	.076	.23	-.838	.379	.03	.106	.188
Dividend	14046	.013	.017	0	.053	0	.005	.02
GDP	14046	2.129	1.458	-9.132	13.396	1.638	2.329	2.855
LGDP	14046	10.785	.338	7.285	11.685	10.76	10.818	10.916

Table 2 presents the Pearson correlations between climate risk and analyst forecast variables, which implies that climate risk has a positive relationship with forecast accuracy and analysts following. Table 3 presents the Pearson correlations between climate risk, cost of debt, forecast accuracy and analysts following. This test indicates that climate risk has a negative relationship with cost of debt and it is opposite to our H1. As shown in Table 2 and Table 3, all control variables have significant correlations with explanatory variables. In addition, except for dependent variables, the variance inflation factors of all other variables are less than 10 which means multicollinearity is not a significant issue.

Table 2 Pearson Correlation Matrix: The Sample of Climate Risk and Analyst Forecast

Variables	FAccuracy	NAnalysts	ACRI	NEstimation	FHorizon
FAccuracy	1.000				
NAnalysts	0.339***	1.000			
ACRI	0.132***	0.113***	1.000		
NEstimation	0.301***	0.934***	0.077***	1.000	
FHorizon	-0.154***	0.084***	-0.039***	0.192***	1.000
Size	0.372***	0.614***	-0.028***	0.632***	-0.030***
Leverage	0.034***	0.204***	0.019***	0.232***	0.023***
PPE	-0.067***	0.049***	-0.198***	0.081***	-0.052***
ROA	0.453***	0.293***	0.025***	0.272***	-0.263***
MTB	0.128***	0.133***	0.082***	0.113***	0.159***
Loss	-0.451***	-0.257***	-0.070***	-0.240***	0.180***
ROE	0.353***	0.210***	0.026***	0.191***	-0.184***
Dividend	0.194***	0.090***	-0.054***	0.105***	-0.022***
GDP	0.065***	-0.005	-0.009*	-0.020***	0.025***
LGDP	0.023***	0.038***	0.198***	0.042***	0.043***

*** *p<0.01, ** p<0.05, * p<0.1*

Table 3 Pearson Correlation Matrix: The Sample of Climate Risk, Cost of Debt, Forecast Accuracy and Analysts Following

Variables	COD	ACRI	F$\widehat{\text{Accuracy}}$	N$\widehat{\text{Analysts}}$	LSize	LMaturity	NLenders	Senior	NAnalysts	NEstimation
COD	1.000									
ACRI	-0.075***	1.000								
F$\widehat{\text{Accuracy}}$	-0.433***	0.124***	1.000							
N$\widehat{\text{Analysts}}$	-0.222***	-0.039***	0.469***	1.000						
LSize	-0.236***	-0.127***	0.295***	0.431***	1.000					
LMaturity	0.133***	0.060***	0.056***	0.025***	0.225***	1.000				
NLenders	-0.311***	-0.033***	0.259***	0.284***	0.587***	0.137***	1.000			
Senior	-0.045***	0.007	0.021**	-0.003	0.001	-0.008	0.032***	1.000		
NAnalysts	-0.221***	0.022**	0.486***	0.933***	0.392***	0.023***	0.265***	0.004	1.000	
NEstimation	-0.184***	-0.033***	0.408***	0.986***	0.416***	0.025***	0.268***	-0.001	0.929***	1.000
FHorizon	-0.046***	-0.110***	0.033***	0.266***	0.249***	0.007	0.120***	0.015*	0.276***	0.343***
Size	-0.278***	-0.175***	0.414***	0.592***	0.689***	0.028***	0.444***	-0.006	0.535***	0.557***
Leverage	0.264***	-0.008	-0.210***	0.016*	0.240***	0.197***	0.089***	-0.003	0.019**	0.051***
PPE	-0.020**	-0.089***	-0.214***	0.030***	0.019**	-0.094***	0.051***	-0.025***	0.032***	0.064***
ROA	-0.290***	0.042***	0.649***	0.129***	0.104***	0.035***	0.129***	0.009	0.122***	0.107***
MTB	-0.112***	0.042***	0.387***	0.172***	0.066***	0.062***	0.006	0.005	0.160***	0.134***
Loss	0.264***	-0.041***	-0.667***	-0.100***	-0.110***	-0.017**	-0.148***	-0.021**	-0.099***	-0.080***
ROE	-0.218***	0.032***	0.500***	0.119***	0.086***	0.019**	0.109***	0.006	0.094***	0.090***
Dividend	-0.237***	-0.033***	0.304***	0.070***	0.137***	-0.044***	0.096***	-0.009	0.077***	0.087***
GDP	-0.175***	-0.018**	0.219***	0.008	0.065***	0.151***	0.079***	0.003	0.017**	-0.020**
LGDP	0.070***	0.284***	0.074***	0.023***	-0.007	0.083***	-0.034***	0.006	0.084***	0.092***

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 3 (continue)

Variables	FHorizon	Size	Leverage	PPE	ROA	MTB	Loss	ROE	Dividend	GDP	LGDP
FHorizon	1.000										
Size	0.311***	1.000									
Leverage	0.121***	0.065***	1.000								
PPE	0.027***	0.064***	0.124***	1.000							
ROA	0.006	0.129***	-0.243***	-0.095***	1.000						
MTB	0.124***	0.035***	0.110***	-0.126***	0.283***	1.000					
Loss	-0.015*	-0.157***	0.135***	0.110***	-0.757***	-0.152***	1.000				
ROE	0.016*	0.160***	-0.086***	-0.073***	0.711***	0.420***	-0.596***	1.000			
Dividend	0.127***	0.179***	0.005	0.031***	0.299***	0.178***	-0.192***	0.217***	1.000		
GDP	-0.029***	0.065***	0.005	0.024***	0.105***	0.081***	-0.087***	0.080***	0.005	1.000	
LGDP	0.004	-0.138***	0.083***	-0.118***	-0.089***	0.058***	0.046***	-0.045***	0.042***	-0.169***	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

4.2 Main Results

The result of the association between climate risk and cost of debt is present in Table 4 Column (1). A positive but non-significant coefficient of climate risk illustrates there is no significant relationship between climate risk and cost of debt. There is no evidence that shows a positive impact of climate risk on cost of debt, which means we cannot accept H1 but also cannot reject it.

Table 4 The Direct Effect of Climate Risk on Cost of Debt and the Moderating Effect of Forecast Accuracy and Analysts Following

	(1) Direct Effect	(2) Moderator: Forecast Accuracy	(3) Moderator: Analysts Following
ACRI	0.0223	0.0010	0.101***
	(0.0143)	(0.0192)	(0.0227)
$\widehat{FAccuracy}$		-4.037***	
		(0.842)	
$ACRI*\widehat{FAccuracy}$		-0.948***	
		(0.362)	
$\widehat{NAnalysts}$			-0.0326***
			(0.0117)
$ACRI*\widehat{NAnalysts}$			-0.0455***
			(0.0097)
LSize	-0.0728***	-0.0733***	-0.0738***
	(0.0049)	(0.0049)	(0.0049)
LMaturity	0.213***	0.213***	0.212***
	(0.0111)	(0.0111)	(0.0111)
NLenders	-0.125***	-0.124***	-0.124***
	(0.0051)	(0.0051)	(0.0051)
Senior	-0.537***	-0.542***	-0.539***
	(0.0869)	(0.087)	(0.0866)
Size	-0.0485***	-0.0202***	-0.0253***
	(0.0053)	(0.0071)	(0.0061)
Leverage	0.918***	0.787***	0.891***
	(0.0329)	(0.0391)	(0.0330)
PPE	-0.218***	-0.248***	-0.217***
	(0.0361)	(0.0365)	(0.0361)
ROA	-0.413***	-0.168**	-0.407***
	(0.0653)	(0.0771)	(0.0652)
MTB	-0.0110***	-0.0026	-0.0083***
	(0.0021)	(0.0025)	(0.0021)
Loss	0.0469***	-0.0274	0.0487***
	(0.0126)	(0.0178)	(0.0125)
ROE	-0.0043	-0.0058	-0.0039
	(0.0204)	(0.0204)	(0.0204)
Dividend	-3.323***	-2.648***	-3.443***
	(0.307)	(0.329)	(0.307)
GDP	-0.0077	-0.0058	-0.0075
	(0.0048)	(0.0049)	(0.0048)
LGDP	-0.0556	-0.0467	-0.0540
	(0.0373)	(0.0382)	(0.0378)
Constant	6.060***	5.660***	5.888***

	(0.444)	(0.457)	(0.449)
Chi-square	8238.197	8298.115	8341.749
Prob > chi2	0.0000	0.0000	0.0000
Number of obs	13948	13948	13948
Industry Dummy	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 The Moderating Effect of Forecast Accuracy and Analysts Following

The mixed-effect analysis results for Equation (3) are shown in Table 5. The coefficient of climate risk is both positive and significant at 1% level in Columns (1) and (2). This indicates that higher climate risk can increase the accuracy of analyst forecasts and the number of analysts following, which aligns with our propositions in Section 2.2. Therefore, using a fitted value of analyst forecast factors as moderators is appropriate and could mitigate endogeneity problems.

Table 5 The Direct Effect of Climate Risk on Forecast Accuracy and Analysts Following

	(1) DV： Forecast Accuracy	(2) DV： Analysts Following
ACRI	0.0027^{***}	0.0454^{***}
	(0.0007)	(0.0030)
FAccuracy		0.496^{***}
		(0.0386)
NAnalysts	0.0091^{***}	
	(0.0007)	
NEstimation	-0.0006	0.729^{***}
	(0.0005)	(0.0019)
FHorizon	-0.0000^{***}	-0.0006^{***}
	(0.0000)	(0.0000)
Size	0.0036^{***}	0.0233^{***}
	(0.0002)	(0.0014)
Leverage	-0.0239^{***}	-0.0753^{***}
	(0.0014)	(0.0105)
PPE	-0.0068^{***}	-0.0663^{***}
	(0.0013)	(0.0097)
ROA	0.0500^{***}	-0.0825^{***}
	(0.0020)	(0.0156)
MTB	0.0016^{***}	0.0138^{***}
	(0.0001)	(0.0007)
Loss	-0.0160^{***}	0.0193^{***}
	(0.0006)	(0.0050)
ROE	0.0005	0.0334^{***}
	(0.0010)	(0.0072)
Dividend	0.151^{***}	-0.854^{***}
	(0.0127)	(0.0979)
GDP	0.0009^{***}	0.0003
	(0.0002)	(0.0016)
LGDP	0.0032^{*}	0.0012
	(0.0018)	(0.0046)
Constant	-0.0811^{***}	-0.931^{***}
	(0.0188)	(0.0698)

Chi-square	19393.60	331946.28
Prob > chi2	0.0000	0.0000
Number of obs	40043	40043
Industry Dummy	Yes	Yes
Year Dummy	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Next, we further explore the moderating role of fitted value of forecast accuracy and analysts following on the association between climate risk and cost of debt by including interaction terms, $ACRI{*}FAc\widehat{cura}cy$ in Equation (4) and $ACRI{*}NAn\widehat{alys}ts$ in Equation (5). The coefficients on $ACRI{*}FAc\widehat{cura}cy$ in Column (2) and $ACRI{*}NAn\widehat{alys}ts$ in Column (3) at Table 4 are all negative and significant at the 1% level, which implies that the effect of climate risk in increasing firms' cost of debt is weakened when the forecast of firm is more accurate or when the number of analysts following increases. Thus, our predictions in H2a and H2b are supported. We also present a two-way moderating effect in Appendix B. According to the figure, the negative association between climate risk and cost of debt is weaker for firms with higher forecast accuracy which is aligning with our propositions.

4.4 The Moderating Effect of Earnings Skewness and Governance Environment

Table 6 shows the results of earnings skewness and governance environment as moderators of the relationship between climate risk and cost of debt. As shown in Table 6, the interaction term in Column (1) has a negative significant coefficient, which proves H3a and indicates a negative moderation effect on the positive association between climate risk and cost of debt. Meanwhile, the coefficient of the interaction term in Column (2) is positive and it is aligning with H3b.

5. Additional Analysis

5.1 Propensity Score Matching

We apply the propensity score matching approach to wipe out the potential selection bias in our study which is that we cannot completely rule out the possibility that the regression results may be shifted by the differences of control variables between the high and low climate risk country groups. According to LaLonde (1986), we first classified countries as high and low climate risk countries as treatment and use its median value of sample as a benchmark, which is 0.6538389 for both samples. We next start with regress ACRI with all other firm-level variables except for our dependent variables. The results for first stage regression are listed in Columns (1) Table 7.

Table 6 The Moderating Effect of Earnings Skewness and Governance Environment

	(1) Moderator: Earnings Skewness	(2) Moderator: Governance Environment
ACRI	0.0339**	0.0280*
	(0.0156)	(0.0157)
$\widehat{SKEW}$	-2.498***	
	(0.803)	
ACRI*$\widehat{SKEW}$	-0.586***	
	(0.189)	
CountPG		0.0160
		(0.0167)
ACRI*CountPG		-0.0234***
		(0.0076)
LSize	-0.0804***	-0.0628***
	(0.0051)	(0.0052)
LMaturity	0.201***	0.300***
	(0.0107)	(0.0112)
NLenders	-0.127***	-0.147***
	(0.0055)	(0.0057)
Senior	-0.567***	-0.675***
	(0.0925)	(0.105)
Size	-0.0584***	-0.0615***
	(0.0059)	(0.0041)
Leverage	0.991***	1.095***
	(0.0353)	(0.0276)
PPE	-0.310***	-0.160***
	(0.0418)	(0.0249)
ROA	-0.324***	-0.619***
	(0.0750)	(0.0688)
MTB	0.0015	-0.0170***
	(0.0042)	(0.0020)
Loss	-0.0925**	0.0824***
	(0.0406)	(0.0136)
ROE	0.100***	0.0442**
	(0.0342)	(0.0221)
Dividend	-3.720***	-4.612***
	(0.338)	(0.253)
GDP	-0.0016	0.0004
	(0.0058)	(0.0052)
LGDP	-0.0423	-0.0371
	(0.0418)	(0.0280)
Constant	5.906***	5.748***
	(0.493)	(0.327)
Chi-square	8598.11	13071.41
Prob > chi2	0.0000	0.0000
Number of obs	13746	14169
Industry Dummy	Yes	Yes
Year Dummy	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

After we obtained an estimation of the propensity score for each observation. Next, we matched the observations categorized by high and low climate risk groups using propensity score with 0.03 caliper under kernel matching and use the matched samples to re-estimate our regression model. The second stage regression results of the main effect are at Column (2) of Table 7 and Columns (3) to (6) for the moderating effect of our tested variables. As expected, there is no significant relationship between climate risk and cost of debt. Whereas the coefficients of ACRI*$\widehat{FAccuracy}$, ACRI*$\widehat{NAnalysts}$, ACRI*$\widehat{SKEW}$ and ACRI*CountPG are negative and significant. To sum up, our primary findings are robust under the propensity score matching approach.

Table 7 The Main Effect of Climate Risk on Cost of Debt and the Moderating Effects: Propensity Score Matching

	(1) First Stage	(2) DV: Cost of Debt	(3) Moderator: Forecast Accuracy	(4) Moderator: Analysts Following	(5) Moderator: Earnings Skewness	(6) Moderator: Governance environment
ACRI		0.0074	-0.0120	0.0954**	0.0218	0.0646*
		(0.0307)	(0.0359)	(0.0454)	(0.0246)	(0.0336)
$\widehat{\text{FAccuracy}}$			-4.381***			
			(1.144)			
ACRI*$\widehat{\text{FAccuracy}}$			-1.047*			
			(0.609)			
$\widehat{\text{NAnalysts}}$				-0.0269		
				(0.0205)		
ACRI*$\widehat{\text{NAnalysts}}$				-0.0490***		
				(0.0174)		
$\widehat{SKEW}$					-2.363***	
					(0.915)	
ACRI*$\widehat{SKEW}$					-0.594**	
					(0.279)	
CountPG						-0.0101
						(0.0246)
ACRI*CountPG						-0.0295**
						(0.0143)
Size	-0.0369***	-0.0602***	-0.0277***	-0.0344***	-0.0669***	-0.0645***
	(0.0029)	(0.0062)	(0.0085)	(0.0072)	(0.0064)	(0.0046)
Leverage	0.0951***	0.948***	0.794***	0.914***	1.046***	1.167***
	(0.0257)	(0.0394)	(0.0476)	(0.0396)	(0.0388)	(0.0309)
PPE	-0.0627***	-0.226***	-0.262***	-0.225***	-0.308***	-0.164***
	(0.0237)	(0.0416)	(0.0422)	(0.0417)	(0.0459)	(0.0286)
ROA	-0.0005	-0.449***	-0.154	-0.433***	-0.410***	-0.685***
	(0.0669)	(0.0850)	(0.100)	(0.0849)	(0.0884)	(0.0804)
MTB	0.0089***	-0.0120***	-0.0023	-0.0086***	0.0011	-0.0153***
	(0.0019)	(0.0026)	(0.0031)	(0.0027)	(0.0048)	(0.0022)
Loss	-0.0282**	0.0622***	-0.0219	0.0653***	-0.0997**	0.0801***
	(0.0130)	(0.0162)	(0.0221)	(0.0161)	(0.0457)	(0.0156)
ROE	-0.0148	-0.0078	-0.0104	-0.0088	0.0976**	0.0260

	(0.0214)	(0.0259)	(0.0259)	(0.0258)	(0.0386)	(0.0247)
Dividend	-0.488**	-3.638***	-2.934***	-3.786***	-3.882***	-4.891***
	(0.241)	(0.364)	(0.390)	(0.365)	(0.373)	(0.286)
GDP	-0.0338***	-0.0012	-0.0001	0.0003	0.00291	0.0103
	(0.0049)	(0.0150)	(0.0153)	(0.0151)	(0.0117)	(0.0106)
LGDP	0.562***	-0.101**	-0.0908*	-0.105**	-0.0506	-0.0584
	(0.0119)	(0.0510)	(0.0536)	(0.0518)	(0.0532)	(0.0439)
LSize		-0.0650***	-0.0656***	-0.0657***	-0.0789***	-0.0672***
		(0.0062)	(0.0062)	(0.0062)	(0.0058)	(0.0059)
LMaturity		0.195***	0.195***	0.194***	0.205***	0.305***
		(0.0141)	(0.0140)	(0.0140)	(0.0122)	(0.0128)
NLenders		-0.119***	-0.119***	-0.118***	-0.133***	-0.150***
		(0.0064)	(0.0064)	(0.0064)	(0.0062)	(0.0065)
Senior		-0.554***	-0.551***	-0.560***	-0.726***	-0.728***
		(0.124)	(0.124)	(0.124)	(0.116)	(0.130)
Constant	-4.424***	6.962***	6.540***	6.801***	6.556***	6.307***
	(0.192)	(0.634)	(0.661)	(0.643)	(0.642)	(0.503)
Chi-square						
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of obs	14046	8958	8958	8958	11049	11371
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Subsample Analyses

To further examine the impact of climate risk on analyst forecast and cost of debt, we conduct two subsample analyses. First, we classified our sample by environmental-sensitive industries and nonenvironmental-sensitive industries according to Patten (2002). It defined chemical, metal, paper and petroleum industries as environmental-sensitive industries. The results of one main effect and two analyst forecast moderating effects based on this subsample are shown in Table 8 and Table 9. There is no significant direct impact of climate risk on cost of debt which is consistent with results of the primary sample. The coefficient of interaction term of climate risk and forecast accuracy is negative and larger for nonenvironmental-sensitive industries as shown in Column (2). However, the coefficient for environmental-sensitive industries is negative and nonsignificant in Column (1). This indicates that for firms in environmental-sensitive industries, cautions and comprehensiveness of analysts' forecasts cannot make a significant impact on the forecast accuracy due to the significant impact of climate change on firms' earnings. High volatility of earnings has an opposite effect on forecast compared to analyst's effort on forecast quality. In addition, the coefficient of climate risk on analysts following is larger in environmental-sensitive industries. Second, we classified our sample into developing countries and developed countries to re-examine three main effects. As in Table 8 and Table 9, the coefficients of climate risk on forecast accuracy and analyst following are all slightly higher in developed countries than in developing countries. This implies the positive effect of climate risk on analyst forecast is enhanced in developed countries.

Table 8 The Main Effect of Climate Risk on Cost of Debt: Subsample Analyses

	DV: Cost of Debt			
	Environmental-sensitive industry		Developed countries	
	Yes	No	Yes	No
ACRI	0.0010	0.0186	0.0035	0.0662**
	(0.0260)	(0.0171)	(0.0190)	(0.0295)
Size	-0.0279	-0.0503***	-0.0495***	-0.113**
	(0.0210)	(0.0055)	(0.0053)	(0.0472)
Leverage	1.065***	0.908***	0.917***	0.866***
	(0.146)	(0.0337)	(0.0330)	(0.310)
PPE	-0.266*	-0.211***	-0.211***	0.0605
	(0.141)	(0.0375)	(0.0365)	(0.323)
ROA	-0.857***	-0.385***	-0.421***	1.941**
	(0.305)	(0.0668)	(0.0655)	(0.950)
MTB	-0.0136	-0.0110***	-0.0108***	-0.0460***
	(0.0101)	(0.0021)	(0.0021)	(0.0168)
Loss	0.0492	0.0481***	0.0451***	0.206**
	(0.0572)	(0.0128)	(0.0127)	(0.103)
ROE	0.108	-0.0116	-0.0026	-0.540*
	(0.0954)	(0.0209)	(0.0205)	(0.289)
Dividend	-3.148***	-3.318***	-3.369***	3.656
	(1.189)	(0.318)	(0.308)	(3.204)
GDP	0.0053	-0.0096*	-0.0226***	-0.0142*
	(0.0126)	(0.0054)	(0.0087)	(0.0082)
LGDP	-0.194***	-0.0019	0.0234	-0.105
	(0.0673)	(0.0479)	(0.0763)	(0.123)
LSize	-0.0932***	-0.0705***	-0.0689***	-0.173***
	(0.0170)	(0.0052)	(0.0050)	(0.0236)
LMaturity	0.310***	0.203***	0.220***	0.0034
	(0.0401)	(0.0115)	(0.0113)	(0.0562)
NLenders	-0.137***	-0.124***	-0.129***	-0.0348
	(0.0187)	(0.0053)	(0.0052)	(0.0287)
Senior	-0.343	-0.559***	-0.539***	0
	(0.277)	(0.0918)	(0.0868)	(.)
Constant	6.909***	5.583***	5.242***	7.882***
	(0.826)	(0.532)	(0.830)	(1.169)
Chi-square	746.19	7555.02	8059.57	416.74
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Number of obs	1163	12785	13631	317
Industry Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9 The Moderating Effects of Forecast Accuracy and Analysts Following: Subsample Analyses

	Moderators: Forecast Accuracy				Moderators: Analysts Following			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Environmental-sensitive industry		Developed countries		Environmental-sensitive industry		Developed countries	
	Yes	No	Yes	No	Yes	No	Yes	No
ACRI	-0.0117	-0.0027	-0.0148	0.0323	0.0225	0.150***	0.108***	0.135**
	(0.0524)	(0.0216)	(0.0232)	(0.0750)	(0.0407)	(0.0295)	(0.0283)	(0.0531)
$\widehat{\text{FAccuracy}}$	5.812**	-5.255***	-4.123***	13.31**				
	(2.871)	(0.887)	(0.865)	(5.748)				
ACRI*$\widehat{\text{FAccuracy}}$	-0.120	-1.038***	-1.185***	0.159				
	(1.123)	(0.388)	(0.388)	(1.767)				
$\widehat{\text{NAnalysts}}$					0.00353	-0.0271**	-0.0286**	0.0691
					(0.0362)	(0.0128)	(0.0126)	(0.0670)
ACRI*$\widehat{\text{NAnalysts}}$					-0.0162	-0.0634***	-0.0533***	-0.0386
					(0.0241)	(0.0113)	(0.0110)	(0.0264)
Size	-0.0687**	-0.0146**	-0.0189***	-0.147***	-0.0251	-0.0243***	-0.0247***	-0.124**
	(0.0281)	(0.0073)	(0.0071)	(0.0535)	(0.0238)	(0.0063)	(0.0061)	(0.0498)
Leverage	1.232***	0.742***	0.774***	1.151***	1.068***	0.875***	0.884***	0.902***
	(0.162)	(0.0403)	(0.0394)	(0.326)	(0.146)	(0.0338)	(0.0331)	(0.306)
PPE	-0.249*	-0.252***	-0.248***	-0.0128	-0.265*	-0.210***	-0.215***	-0.208
	(0.140)	(0.0380)	(0.0369)	(0.327)	(0.141)	(0.0376)	(0.0365)	(0.308)
ROA	-1.142***	-0.0709	-0.161**	1.408	-0.851***	-0.378***	-0.413***	1.977**
	(0.334)	(0.0794)	(0.0777)	(0.965)	(0.305)	(0.0666)	(0.0654)	(0.948)
MTB	-0.0232**	-0.0003	-0.0020	-0.0599***	-0.0134	-0.0081***	-0.0081***	-0.0398**
	(0.0112)	(0.0026)	(0.0025)	(0.0199)	(0.0103)	(0.0021)	(0.0021)	(0.0176)
Loss	0.140**	-0.0475***	-0.0336*	0.510***	0.0503	0.0497***	0.0479***	0.280***
	(0.0702)	(0.0184)	(0.0180)	(0.140)	(0.0573)	(0.0128)	(0.0126)	(0.104)
ROE	0.106	-0.0150	-0.0046	-0.508*	0.112	-0.0113	-0.0021	-0.470
	(0.0956)	(0.0208)	(0.0205)	(0.289)	(0.0955)	(0.0208)	(0.0205)	(0.292)
Dividend	-4.240***	-2.484***	-2.626***	0.700	-3.144***	-3.502***	-3.461***	3.499
	(1.316)	(0.340)	(0.332)	(3.547)	(1.191)	(0.318)	(0.308)	(3.284)
GDP	-0.0024	-0.0070	-0.0218**	-0.0260**	0.0048	-0.0094*	-0.0189**	-0.0100
	(0.0136)	(0.0055)	(0.0085)	(0.0103)	(0.0127)	(0.0054)	(0.0085)	(0.0081)
LGDP	-0.194**	0.0195	0.0315	0.0197	-0.188***	0.0016	0.0153	0.117
	(0.0754)	(0.0487)	(0.0676)	(0.110)	(0.0677)	(0.0491)	(0.0666)	(0.103)
LSize	-0.0949***	-0.0713***	-0.0697***	-0.191***	-0.0937***	-0.0714***	-0.0699***	-0.187***
	(0.0169)	(0.0051)	(0.0050)	(0.0242)	(0.0170)	(0.0051)	(0.0050)	(0.0243)
LMaturity	0.311***	0.203***	0.220***	-0.0324	0.308***	0.203***	0.220***	-0.0294

	(0.0401)	(0.0115)	(0.0113)	(0.0565)	(0.0403)	(0.0115)	(0.0113)	(0.0575)
NLenders	-0.136***	-0.123***	-0.128***	-0.0326	-0.137***	-0.122***	-0.127***	-0.0336
	(0.0186)	(0.0053)	(0.0052)	(0.0292)	(0.0187)	(0.0053)	(0.0052)	(0.0294)
Senior	-0.335	-0.564***	-0.542***	0	-0.340	-0.562***	-0.538***	0
	(0.277)	(0.0915)	(0.0867)	(.)	(0.277)	(0.0913)	(0.0866)	(.)
Constant	7.430***	4.973***	4.834***	7.852***	6.827***	5.362***	5.129***	6.300***
	(0.914)	(0.545)	(0.740)	(1.202)	(0.833)	(0.543)	(0.727)	(1.013)
Chi-square	757.48	7638.89	8127.09	404.89	747.47	7682.60	8168.39	412.36
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of obs	1163	12785	13631	317	1163	12785	13631	317
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6. Conclusion

As literature research on climate risk and firm performance is increasing, our study provides a new direction by including firm financing activities into consideration. We use cost of debt and analyst forecast factors to capture how climate risk can impact firm financing activities. As the results are shown in last section, we observe a nonsignificant relationship between climate risk and cost of debt. This means there is no direct impact of country-level climate risk on firms' cost of debt. However, we find analyst forecasts may have an influence on this relationship. To start with, we examine the relationship between climate risk and analyst forecast and find with higher climate risk, the accuracy of forecasts and the number of analysts following one firm will both increased. Therefore, invest in a high climate risk area may not be a risky decision for investors. Although low-climate-risk firms may have a more stable environment to ensure steady performance, investing in high-climate-risk firms may lead to higher returns as people tend to overestimate their default risk.

In addition, we also investigate the moderating role of forecast accuracy and analysts following on the relationship between climate risk and cost of debt. And find they can weaken their relationship. High climate risk may lead to a higher cost of debt but with high forecast accuracy or a large number of analysts following, the cost from information asymmetry can be mitigated and eventually reduced cost of debt. Also, with the monitoring effect of analyst forecast, managers will be cautious when using risk-taking projects or management to hedge the risk from climate change, which eventually reduces the default risk by making prudent decisions and then reduce cost of debt even under high climate risk.

Implications of this study include both academic and practical perspectives. From an academic perspective, this article expands firm financing research by exploring the relationship between climate risk and firm financing behavior. By bring external conditions in financing activities, it provides a more comprehensive and climate risk management that has impacts on financing activities. This helps future researchers including sustainable management in their financing studies. Also, this study enriches climate risk literature by adding analyst forecast and cost of debt into consideration. From a practical perspective, this article provides a new side of climate risk. Instead of treating climate risk as a negative factor of firm performance, we think it can enhance the quality of analyst forecast and therefore reduce the loss for investors. Firms under high climate risk could also treat it as a new condition to attract market participants' attention. In addition, except earning profit through well management and operation, firms should also be aware of the change of environment surrounded and figure out how they can adapt to those fast climate changes.

We also conclude several limitations and future research directions. First, we only discussed cost of debt and analyst forecast factors to examine firms' financing activities. Even more factors could be included in the topic of climate risk and financing activities. For example, we could use the statement of cash flows data to capture the net amount of cash generated by corporate financing activities based on the study of Bradshaw, Richardson and Sloan (2006). Moreover, instead of only looking at internal explanations, we suggest exploring more external risks that can alter or affect firm financing activities. For example, we can study whether country-level or region-level crime rates or the COVID19 pandemic can directly or indirectly relate to firm financing. Second, although we examine the positive or negative effects of climate risk empirically, how firms should deal with climate risk practically is not fully discussed. With the increasing severity of climate changes, it is essential for firms to seek strategies to adapt to these frequent changes in environment. What strategies firms can pursue to avoid damage of climate change and what strategies firms can apply to recover from the damage caused by climate risk rapidly so that the decrease of firm performance can be controlled are still awaiting investigation. Third, this study only analyses debt as a representative of firm financing indicators. Yet researchers think that cost of debt could trigger the changes in firms' capital structure (Meng & Yin, 2019; Bolton & Freixas, 2000). What is the role of climate risk and analyst forecast in capital structure changes needs further study?

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Appendix A Variable Description

Variables	Description
Independent variable	
CRI	Global Climate Risk Index (CRI) from 2004 to 2018 on Germanwatch
Dependent variables	
FAccuracy	FAccuracy is the negative value of the absolute difference between an analyst's earnings forecast and the actual earnings (i.e., Forecast EPS - Actual EPS) divided by the stock price at the beginning of the year.
NAnalysts	Log of Number of analysts following a firm in that year
COD	Log of the loan spread using all-in-drawn approach
Loan-related firm-level	
LMaturity	The natural log of the time till loan maturity, in days
LSize	The natural log of total loan value of the facility (in USD)
Senior	1 if the loan is senior and 0 other wise
NLenders	Numbers of lenders participating
Forecast-related firm-level	
NEstimation	Log of Number of estimates of a firm in that year
FHorizon	The median forecast horizon (the number of days between earnings announcement date and forecast date) of analyst forecasts for each firm each year.
Country-level variables	
GDP	annual growth of total GDP
LGDP	log of real GDP per capita
CountPG	Governance environment. The sum of total score from two dimensions of country-level governance: political stability and government effectiveness.
Firm-level variables	
Skewness	the mean–median difference of EPS deflated by the stock price or skewness coefficient
Size	The natural log of total assets at year-end
Leverage	Long-term debt divided by total assets
PPE	Net property, plant and equipment divided by total assets at year-end
ROA	Earnings before extraordinary item divided by average total assets at year-end
MTB	
ROE	Net income/Stockholders equity
Loss	equals 1 if the firm reports negative earnings in the year, and 0 otherwise
Dividend	Dividend divided by total assets at year-end

Appendix B Two-way Moderating Effect of Forecast Accuracy and Analysts Following