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The impact of climate risk on firm performance and financing choices: An international comparison

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Abstract

Increasingly adverse climatic conditions have created greater systematic risk for companies throughout the global economy. Few studies have directly examined the consequences of climate-related risk on financing choices by publicly listed firms across the globe. We attempt to do so using the Global Climate Risk Index compiled and published by Germanwatch (Kreft & Eckstein, 2014), which captures at the country level the extent of losses from extreme weather events. As expected, we find the likelihood of loss from major storms, flooding, heat waves, etc. to be associated with lower and more volatile earnings and cash flows. Consistent with policies that attempt to moderate such effects, we show that firms located in countries characterized by more severe weather are likelier to hold more cash so as to build financial slack and thereby organizational resilience to climatic threats. Those firms also tend to have less short-term debt but more long-term debt, and to be less likely to distribute cash dividends. In addition, we find that certain industries are less vulnerable to extreme weather and so face less climate-related risk. Our results are robust to using an instrumental variable approach, a propensity-score-matched sample, and path analysis, and remain unchanged when we consider an alternative measure of climate risk. Finally, our conclusions are invariant to the timing of financial crises that can affect different countries at different times.

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INTRODUCTION

The effect of climate on economic performance has long been recognized and documented (e.g., Dell, Jones, & Olken, 2014; Gallup, Sachs, & Mellinger, 1999; Nordhaus, 2006). Studies have generally focused on the economic impact of climatic events on geographic units (countries and municipalities). Concern about worldwide changes in climate has also led to an examination of the impact of the environment on firm valuation (e.g., Beatty & Shimshack, 2010; Chava, 2014; Konar & Cohen, 2001; Matsumura, Prakash, & Vera-Munoz, 2014). Those studies generally consider regulatory and environmental risks associated with carbon dioxide

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emissions and other pollutants. We are not aware of any work that directly examines the effect of climate on publicly listed firms. Moreover, few studies have addressed whether and to what extent managers of public firms worldwide weigh the risk of extreme weather shocks when formulating financial policies.[1] Yet managers are likely to be influenced by *climate risk*, that is, losses from major weather events such as storms, floods, and heat waves, because they cannot obtain full insurance coverage against it.[2]

We use a cross-country empirical setting to examine the effect of climate risk on the financing and performance of publicly traded firms around the globe. Our proxy for climate risk is the Global Climate Risk Index (hereafter CRI) compiled and published by the non-profit, non-governmental organization Germanwatch (Kreft & Eckstein, 2014), which provides a quantified measure by country of extreme weather-related economic losses. This measure is also indicative of future extreme weather events (Kreft & Eckstein, 2014). Our study is based on both a long-term CRI score for the years 1993–2012 and seven annual CRI scores for the years 2006–2012. According to Kreft and Eckstein (2014), from 1992 to 2011 extreme weather events led to more than 530,000 casualties and economic losses of over 2.5 trillion USD at purchasing power parity (PPP). There is also anecdotal evidence of significantly negative effects of extreme weather on firm performance. For example, in Hurricane Katrina's aftermath, many chemical firms experienced lower earnings due to surging energy costs and lost production facilities (Reisch, 2005).

Our sample consists of 353,906 firm-years from 55 countries over 20 years from 1993 to 2012. Table 1 gives the distribution of firm-years by country. We control for firm-level factors (e.g., size, age, assets, and growth) and country-level factors (e.g., GDP, GDP growth, and legal environment). As expected, we find that firms in countries with higher climate risk have poorer economic performance as measured by return-on-assets (*ROA*) and cash flows from operations over assets (*CFO*). Moving from the first quartile to the more risky third quartile of the annual CRI score can reduce a firm's *ROA* by 1.8 percentage points. We find also that firms in countries experiencing higher climate risk have more volatile earnings, measured by both accounting earnings and operating cash flows. This is consistent with extreme weather events disrupting business operations and bringing about fluctuations in earnings and operating cash flows.

Next, we examine whether climate risk is anticipated by managers and if it leads them to make changes in financing policies. Diamond (1991) and Bates, Kahle, and Stulz (2009) find that policies on debt and cash holdings are driven by liquidity concerns. We expect and find that firm managers in environments characterized by higher climate risk are concerned about being able to repay their creditors should an extreme weather event occur that inflicts considerable losses and hence rely less on short-term and more on long-term borrowing. We find that they are also likely to hold more cash and to issue lower cash dividends. These results suggest that firms use financing policies to hedge against operating cash flow volatility and illiquidity due to higher climate risk. However, we also find that the effect of climate risk on firm performance varies across industries, as climate risk has a more negative impact on some than on others.

We conduct an array of robustness tests. To mitigate concern about the omission of country-level control variables, we use the instrumental variable approach and continue to find similar results. We also use propensity scores to match observations on firm characteristics. The results remain robust. They are also robust to other factors such as whether or not the firm has climate risk insurance coverage and whether it is a multinational firm. We also test for alternative measures of climate-related risk, for the exclusion of US firms from the sample, and for the inclusion of CRI subindicators one at a time.

Our research makes at least two important contributions. To the best of our knowledge, it is the first study on the direct impact of the risk of major weather events on public firm performance in a cross-country setting. We find that firms in countries that face higher climate risk have significantly lower and more volatile earnings and cash flows. Thus, climate risk represents a significant exogenous source of earnings and cash volatility, along with economy, industry, and accounting factors (e.g., uncertainty surrounding accounting estimates) (Dichev & Tang, 2009; Lipe, 1990). This finding is also relevant to the literature on the effect of earnings volatility on firm operations and valuation (e.g., Francis, LaFond, Olsson, & Schipper, 2004; Minton & Schrand, 1999; Ronen & Sadan, 1981; Rountree, Weston, & Allayannis, 2008).

Table 1 Country-level variable measures by country

Country name	Long-term climate risk index (years 1993–2012)	Annual average number of deaths (years 1993–2012)	Annual average number of deaths per 100,000 inhabitants (years 1993–2012)	Annual average losses in US $PPP (years 1993–2012)	Annual average losses per unit GDP in % (years 1993–2012)	Standard deviation of climate risk index (annual)	Annual average LGDP	Annual average GDP growth	LEG_ENV	Number of observations (total 353,906 obs.)
Argentina	−88.5	20.60	0.05	533.90	0.12	12.69	8.98	0.07	2.34	705
Australia	−52.2	46.95	0.23	1702.00	0.24	15.03	10.46	0.11	2.57	15,063
Austria	−61.8	26.90	0.33	382.90	0.15	25.36	10.41	0.04	2.22	1253
Bangladesh	−19.7	816.40	0.56	1833.00	1.16	18.69	6.40	0.10	0.19	179
Belgium	−71.5	86.25	0.82	93.55	0.03	12.75	10.39	0.05	2.16	1552
Brazil	−87	154.00	0.09	761.40	0.04	30.46	8.61	0.09	2.22	3483
Bulgaria	−87	7.30	0.09	142.40	0.16	22.58	8.53	0.12	1.66	142
Canada	−102.2	10.90	0.03	861.20	0.08	10.81	10.34	0.07	2.83	12,929
Chile	−106.5	8.60	0.05	132.50	0.07	23.83	8.94	0.09	1.85	1650
China	−42.3	1820.00	0.14	28,927.00	0.49	8.62	7.68	0.17	2.78	25,256
Colombia	−54.2	111.30	0.27	608.10	0.18	23.10	8.18	0.11	1.03	286
Croatia	−59.2	35.15	0.79	86.52	0.13	18.84	9.27	0.06	1.48	261
Czech	−71.2	9.80	0.09	586.40	0.26	21.54	9.22	0.08	0.41	145
Denmark	−115.3	0.80	0.01	215.30	0.13	18.31	10.64	0.04	1.93	1996
Ecuador	−44.3	64.30	0.49	261.70	0.30	32.03	8.24	0.12	2.51	19
Finland	−154.2	0.20	0.00	22.03	0.02	24.27	10.42	0.05	4.08	1856
France	−42.7	959.00	1.59	1623.00	0.09	14.06	10.33	0.04	3.96	9853
Germany	−48	476.30	0.58	2264.00	0.09	11.99	10.37	0.03	2.18	9826
Greece	−84.3	13.50	0.12	249.90	0.10	26.59	9.96	0.05	1.83	2128
Hong Kong	−175.5	0.00	0.00	0.00	0.00	13.17	10.29	0.04	2.86	3117
Hungary	−68	34.75	0.34	173.90	0.11	7.07	9.05	0.08	3.56	239
India	−74.7	246.20	0.12	744.60	0.09	19.81	7.32	0.14	1.02	3662
Indonesia	−38.5	3142.00	0.30	6236.00	0.26	12.34	6.74	0.12	−0.41	25,747
Ireland	−121.2	2.00	0.05	67.44	0.05	17.78	10.44	0.08	2.91	880
Israel	−121.7	4.35	0.07	39.46	0.03	28.54	10.09	0.08	0.98	2145
Italy	−40.7	1003.00	1.73	1564.00	0.10	18.18	10.25	0.04	0.74	3082
Jamaica	−60.5	4.75	0.18	173.00	0.85	22.58	8.36	0.05	1.51	176
Japan	−92	76.25	0.06	1663.00	0.05	15.34	10.52	0.02	3.19	49,376
Lithuania	−80.5	4.50	0.19	59.53	0.19	26.81	9.15	0.12	3.19	244
Malaysia	−85.2	43.70	0.18	163.80	0.06	24.27	8.68	0.10	1.44	11,095
Mexico	−57.7	140.80	0.14	2377.00	0.19	13.85	8.87	0.07	3.09	1534
Morocco	−86.7	31.50	0.11	111.90	0.11	0.00	7.71	0.08	1.93	540
Netherlands	−74.3	84.65	0.53	151.10	0.03	14.03	10.40	0.05	1.31	2506
New Zealand	−83.3	3.40	0.08	224.70	0.23	19.67	10.08	0.09	2.75	1310
Norway	−134.2	1.55	0.03	50.65	0.02	23.96	10.98	0.08	3.24	2560
Pakistan	−31.8	469.90	0.32	2395.00	0.74	21.08	6.66	0.09	2.11	2257
Panama	−95.3	8.80	0.29	16.26	0.06	18.10	8.88	0.13	−0.87	14

Table 1 (*Continued*)

Country name	Long-term climate risk index (years 1993–2012)	Annual average number of deaths (years 1993–2012)	Annual average number of deaths per 100,000 inhabitants (years 1993–2012)	Annual average losses in US $PPP (years 1993–2012)	Annual average losses per unit GDP in % (years 1993–2012)	Standard deviation of climate risk index (annual)	Annual average LGDP	Annual average GDP growth	LEG_ENV	Number of observations (total 353,906 obs.)
Peru	−63.7	109.20	0.42	171.00	0.09	20.00	8.08	0.10	2.74	819
Philippines	−31.2	643.40	0.79	736.30	0.29	15.92	7.26	0.09	2.04	1625
Poland	−66.5	52.20	0.14	859.00	0.16	22.19	9.17	0.09	1.91	3313
Portugal	−37.3	142.60	1.38	404.90	0.20	30.65	9.68	0.04	2.47	756
Russia	−43.5	2962.00	2.04	1727.00	0.08	28.78	8.85	0.18	3.24	1208
Singapore	−168.5	0.10	0.00	2.48	0.00	19.22	10.41	0.10	3.86	7185
Slovakia	−99.7	4.50	0.08	99.88	0.10	15.39	9.11	0.09	1.58	68
Slovenia	−61.2	11.95	0.60	76.69	0.18	16.53	9.76	0.07	0.60	268
South Africa	−85.7	62.25	0.14	212.90	0.05	13.61	8.44	0.08	1.25	3167
Spain	−48.5	704.70	1.67	783.70	0.07	8.73	9.95	0.05	2.10	1913
Sweden	−129.5	1.25	0.01	138.10	0.05	14.69	10.58	0.05	2.17	4979
Switzerland	−48.5	56.15	0.76	389.20	0.15	20.42	10.82	0.05	2.92	3076
Thailand	−31.5	160.30	0.26	5410.00	1.29	23.00	8.06	0.08	3.04	5230
Turkey	−104.2	40.65	0.06	202.60	0.03	19.69	8.89	0.11	2.45	1523
USA	−44.8	486.10	0.17	38,827.00	0.35	8.42	10.55	0.05	4.28	96,841
United Kingdom	−68.7	117.30	0.20	1415.00	0.08	11.03	10.34	0.05	1.89	21,537
Venezuela	−64	68.90	0.27	344.10	0.11	22.29	8.75	0.14	0.66	135
Vietnam	−24	419.70	0.52	1637.00	0.91	10.61	7.16	0.15	3.11	1197

Second, we establish a link between global climate risk and firm financing policies. Prior literature shows that liquidity risk affects firm financial policies on debt, cash holdings, and cash dividend issuance (e.g., Bates et al., 2009; Diamond, 1991; Stulz, 1990; Wang, 2012). For example, holding cash can be a risk management tool against cash fluctuations (Bates et al., 2009). Our findings suggest that firms facing higher climate risk have less short-term but more long-term debt, hold more cash, and distribute lower cash dividends. Our results also suggest that holding more cash to create financial slack is one way for firms to maintain organizational resilience to climate risk.

The remainder of the article is organized as follows. We begin the next section with a literature review and then develop hypotheses. We then explain our climate risk measures and describe our sample. Then, we discuss the methodology, give descriptive statistics, and present our analyses on the effect of climate risk on financial performance, earnings volatility, and cash volatility. We present the results of robustness tests in the penultimate section, and our conclusions in the final section.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Effect of Climate Risk on Financial Performance and Earnings Volatility

It has long been recognized that climate can substantially impact a country's economic performance (Dell et al., 2014). For example, Nordhaus (2006) shows that climate is a key variable in explaining per capita income differences between Africa and wealthier regions of the world. One main measure of climate is temperature. Gallup et al. (1999), Bansal and Ochoa (2012), and Dell, Jones, and Olken (2009) show a negative relationship between temperature and economic performance. Specifically, Gallup et al. (1999) and Bansal and Ochoa (2012) find that countries in warmer regions are typically poorer per capita than their counterparts in cooler climates and that their economies and equity markets grow more slowly.[3] Burke, Hsiang, and Miguel (2015) present strong evidence that the productivity of countries increases along with increases in temperature until an annual average temperature of 13 °C, with productivity declining significantly at higher temperatures, suggesting a non-linear relationship between economic productivity and temperature. In a study based on US municipal-level data, Dell et al. (2009) find a negative association between temperature and economic output.[4]

The above studies suggest that ongoing climate change will negatively affect economic activities and outputs as average temperatures rise (IPCC, 2007).[5] Burke et al. (2015) write that by 2100 unmitigated warming could reduce average global income by about 23%, Fuss (2016) that climate change destroys financial assets and disrupts related economic activities, and Covington and Thamotheram (2015) that a diversified global stock portfolio will lose 5–20% of its value if warming reaches 4 °C or more.

The amount of daylight associated with seasonality can also affect human psychology and mood with concomitant effects on economic behavior. For example, Kamstra, Kramer, and Levi (2003) find that "seasonal affective disorder" affects stock returns.[6] Hirshleifer and Shumway (2003) find that sunny weather makes traders more upbeat which leads to positive stock returns, and Cao and Wei (2005) that higher temperature is associated with apathy and lower stock returns and lower temperature with aggressiveness and higher stock returns.[7] Similarly, Novy-Marx (2014) points to the effect of New York City temperatures on stock returns.

Prior studies have also examined the effect of extreme weather events on the economy. Kreft and Eckstein (2014) state that global extreme weather events over the 1993–2012 period led to more than 530,000 casualties and over $2.5 trillion in economic losses. Jahn (2013) shows that from 1980 to 2012 the number of extreme weather events and losses from them increased significantly worldwide. Based on the 1970–2002 cross-country data, Yang (2008) shows that stronger storms are associated with higher fatalities and economic losses. Similarly, Hsiang and Narita (2012) show that extreme weather events such as windstorms lead to reduced growth rates as well as economic losses. Based on data from 28 Caribbean nations, Hsiang (2010) finds that while cyclones have a significant negative impact on some industries, they can have a significant positive impact on others, for example, on the construction industry. In a within-country study, Deryugina (2011) finds that government aid mitigates the economic losses from hurricanes and, as a result, there is no significant effect on county-level earnings ten years after their occurrence.[8]

In sum, although many studies have presented evidence of climate and climate-related factors having an economic impact within and across countries, there is a lack of direct evidence of an impact at the firm level, which would be very useful in understanding its impact on managerial decisions and firm performance. Extreme weather can negatively affect firm performance because it can inflict physical damage on firm fixed assets (e.g., property, plant, and equipment), decreasing not only the value of the assets, but also the earnings that might have been generated from them. Given the sometimes significant negative effect of extreme weather conditions on local economies, firm property, and business operations, we present the following hypothesis:

Hypothesis 1: Climate risk is negatively (positively) associated with a firm's financial returns (earnings volatility).

Effect of Climate Risk on Financial Policy

Climate change and increasingly extreme weather necessitate substantial organizational transformations (Wilbanks et al., 2007). A large body of literature addresses the notion of organizational resilience to climate change, which is the ability of an organization to systematically absorb, and recover from, the adverse effects of external environmental disturbance caused by weather extremes (Berkes, Colding, & Folke, 2003; Linnenluecke & Griffiths, 2010; Tschakert & Dietrich, 2010). Studies focus mainly on operational resilience to climate change, through relocation of activities, improvements in infrastructure and production techniques, and increased insurance coverage (Berkhout, Hertin, & Gann, 2006; Hoffmann, Sprengel, Ziegler, Kolb, & Abegg, 2009). Some point to the importance of organizational slack resources, such as backup facilities and financial slack (e.g., Linnenluecke, Griffiths, & Winn, 2008; Vogus & Sutcliffe, 2007; Woods, 2006). However, more studies are needed on financial slack (Linnenluecke & Griffiths, 2010). We expect that firms in countries characterized by extreme weather are more likely to maintain financial slack resources in order to improve organizational resilience to weather extremes.

Effect of climate risk on debt

Given our predicted effects of climate risk (i.e., reducing firm performance and increasing earnings volatility), we expect that firms located where extreme weather events are likely will increase financial slack resources. Debt structure is an important financial policy of this kind. Diamond (1991) posits that firms with high liquidation risk are likely to prefer long-term debt due to short-term illiquidity concerns. Hence, high cash flow volatility and the accompanying liquidation risk are likely to cause firms to take on less short-term debt. In addition, because short-term debt is subject to more frequent renegotiation it is more likely to be negatively affected by liquidity shocks (Custodio, Ferreira, & Laureano, 2013). Extreme weather can lead to liquidity shocks, and thus firms in areas characterized by extreme weather may prefer long-term debt to avoid financial constraints.[9]

Based on the above discussion, we present the following hypotheses:

Hypothesis 2: Climate risk is positively associated with firm long-term debt.

Hypothesis 3: Climate risk is negatively associated with firm short-term debt.

Effect of Climate Risk on Cash Holding

The precautionary motive is an important reason for holding cash (e.g., Bates et al., 2009; Huang, Wu, Yu, & Zhang, 2015; Opler, Pinkowitz, Stulz, & Williamson, 1999). Opler et al. (1999) find that firms are inclined to hold more cash when performance is poor or cash flow volatility is high, suggesting that firms hold more cash to cope with adverse shocks. As country-level climate risk is an adverse shock to firm operation, those in higher climate risk environments have incentives to hold more cash.

Prior studies show that high cash flow volatility leads firms to hold more cash (e.g., by paying lower cash dividends) as a hedge against operational risk (Itzkowitz, 2013; Larkin, 2013; Wang, 2012). For example, Wang (2012) shows that because losing a major customer can lead to a huge drop in cash inflow, firms tend to hold cash as a hedge against that. As we discuss above, climate risk can increase operational risk (e.g., performance volatility) and lead firms to hold more cash.

Based on the above discussion, we present the following hypotheses:

Hypothesis 4: Climate risk is positively associated with cash holding.

Hypothesis 5: Climate risk is negatively associated with cash dividends.

MEASUREMENT AND SAMPLE DATA

Measurement

We use the 2014 Global Climate Risk Index (CRI) compiled and published by Germanwatch to measure climate risk by country.[10] The CRI captures the extent to which countries have suffered direct loss associated with extreme weather-related events such as storms, floods, and heat waves (Kreft & Eckstein, 2014).[11] According to the authors, the CRI is indicative of the severity of the climate risk a country faces in the future due to climate change (Kreft & Eckstein, 2014: 3). The CRI has been widely cited by studies addressing climate change (e.g., Burnell, 2012; Rivera & Wamsler, 2014; Garschagen & Romero-Lankao, 2015), and recent scientific evidence shows that many severe weather events are attributable to climate change (Jahn, 2013; Kreft & Eckstein, 2014).

The CRI has been published annually since 2006, the 2014 edition being the ninth and most recent. There are two sets of CRI scores: annual and long-term. Annual scores are based on data pre-dating by 2 years the edition year. For example, the 2014 edition contains annual scores based on 2012 data. The long-term scores are based on data for a period of 20 years ending 2 years prior to the edition year, e.g., the long-term scores in the 2014 edition are based on the 1993–2012 data. We adopt annual scores from the 2008 to 2014 editions and the 2014 edition long-term scores.[12] That is, we use annual data, 2006–2012, and long-term data for the period 1993–2012.

The CRI is based on the following two absolute and two relative indicators of climate-related risk: (1) number of deaths, (2) number of deaths per 100,000 inhabitants, (3) sum of losses in US$ at purchasing power parity (PPP), and (4) losses per unit of Gross Domestic Product (GDP).[13] A country's index score equals that country's average ranking of all four indicators, absolute indicators (1) and (3) weighting one-sixth each, and relative indicators (2) and (4) weighting one-third each.[14] Lower index scores and the corresponding higher rankings thus indicate greater risk. For example, in the 2014 edition, Honduras has the lowest long-term CRI score of 10.17, derived from the rankings in the four indicators. Honduras is ranked Number 1 on the CRI with the most severe climate-related risk during 1993–2012. Since lower index scores indicate higher climate risk, we multiply the index scores by negative one so that higher scores indicate greater risk. For example, the Honduras score becomes −10.17.

Data

Table 1 shows the number of observations by country. There are a total of 353,906 observations, 27% of which come from the US (96,841 observations). We obtained financial data for these firms from Compustat and country-level institutional data from a number of sources (see the Appendix for details). Following the extant literature (e.g., Masulis & Mobbs, 2014), we exclude the financial and utility industries from our sample since these industries are highly regulated and are quite different from other industries. The country sample size varies between 54 and 55 countries depending on data availability.[15] Table 1 presents the descriptive statistics for country-level variables for 55 countries. Vietnam, the Philippines, Thailand, and Portugal have the highest (i.e., the least negative) long-term CRI scores: they suffered the most direct losses from weather-related events over the 1993–2012 time period. For example, in the case of Vietnam the annual average number of deaths is given as 419.70 (0.52 deaths per 100,000 inhabitants) and the annual average loss in purchasing power as \$1637 million (0.91% of their GDP). Ecuador has the highest standard deviation of annual CRI (32.03). Norway, Switzerland, Denmark, Sweden, and the US are ranked the highest in terms of GDP, and Russia, China, Vietnam, India, and Venezuela ranked the highest in GDP growth. In terms of legal environment (*LEG_ENV*), the US, Finland, France, Singapore, and Hungary are ranked the highest.

METHODOLOGY AND DESCRIPTIVE STATISTICS

Methodology

We estimate the effect of climate risk on financial performance, on earnings and operating cash flow volatility, and on financial policy using the following specification:

$$\begin{aligned} &\text{Financial performance/performance volatility/} \\ &\quad \text{financial policy} = \beta_0 + \beta_1 \text{Climate Risk} \\ &\quad + \beta_2 ROA/CFO + \beta_3 SIZE + \beta_4 Ln(age) \\ &\quad + \beta_5 Intangible\ Assets + \beta_6 PPE + \beta_7 Total\ Debt \\ &\quad + \beta_8 Sales\ Growth + \beta_9 LGDP + \beta_{10} GDP\ Growth \\ &\quad + \beta_{11} LEG\_ENV + Industry + Year + \varepsilon. \qquad (1) \end{aligned}$$

The dependent variables are two measures of financial performance, two of earnings and operating cash flow volatility, and five of financial policies. Financial performance is measured by return-on-assets (*ROA*) and cash flows from operations (*CFO*); hence, *ROA/CFO* is not included in the control variables when testing the effect of climate risk on financial performance. *Earnings Volatility* is the standard deviation of quarterly pre-tax income scaled by total assets over the preceding five fiscal years and *Operating Cash Flow Volatility* is the standard deviation of quarterly cash flows from operations scaled by total assets over the preceding five fiscal years. Financial policy is measured by three measures of debt, *Short-term Debt*, *Long-term Debt*, and *Short and Long-term Debt*, by *Cash Holding* (cash and short-term investment scaled by lagged assets), and by *Cash Dividend* (cash dividend scaled by lagged assets). The variable of interest is *Climate Risk*, measured by annual and long-term CRI scores published by Germanwatch as described previously. The Appendix provides the variable definitions.

We control for firm characteristics including the natural log of assets (*SIZE*), the natural log of firm age (*Ln*(*age*)), intangible assets (*Intangible Assets*), net property, plant, and equipment (*PPE*), *Total Debt*, and *Sales Growth*.

The country-level macroeconomic factors we include in the regression model are log of real GDP per capita (*LGDP*) and annual growth of total GDP (*GDP Growth*), to follow previous study (Kingsley & Graham, 2017). Since CRI is likely to be affected by the size and financial performance of a country's economy, we also use *LGDP* and *GDP growth* to control for these factors. To control for a country's legal environment, we use *LEG_ENV*, the principal component extracted from *COMMON*, *ENFORCE*, and *CR*. *COMMON* refers to an indicator by La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1998) that equals one if the legal origin is common law, and zero otherwise; *ENFORCE* is the law enforcement index (from the Economic Freedom of the World 2010 Annual Report) that ranges from 0 to 10, with higher values indicating greater law enforcement. *CR* is an index reflecting creditor rights, which is formed by adding four dummy variables: a dummy equal to one (1) when a country imposes restrictions, such as creditor consent or minimum dividends to file for reorganization; (2) when secured creditors are able to gain possession of their security once a reorganization petition has been approved (no automatic stay); (3) when secured creditors are ranked first in the distribution of proceeds that result from the disposition of the assets of a bankruptcy; and (4) when debtors do not retain the administration of their property pending the resolution of the reorganization. The index ranges from 0 to 4 and is based on La Porta et al. (1998) and Djankov, McLiesh, and Shleifer (2007).

Following prior literature (Le & Kroll, 2017; Marano, Tashman, & Kostova, 2017), we control industries and year fixed effects.

Descriptive Statistics

Table 2, Panel A shows the descriptive statistics for the sample used for testing for the effect of climate risk on firm performance, earnings volatility, and financial policy.[16] The required data to be included in these tests are available for a total of 55 countries, those listed in Table 1. The mean and median annual climate risks are −44.53 and −38.00, respectively, −65.59 for the annual score, and −48.00 for the long-term score. Our sample firms have a median *ROA* of 0.040, a *CFO* of 0.061, a short-term debt of 0.052, cash holdings of 10.4% of assets, and cash dividends of 0.6% of assets. The natural log of their assets (*Size*) is 6.28, the natural log of firm age (*Ln*(*age*)) is 2.197, and sales growth is 7.5%. The median value of the log of a country's per capita GDP (*LGDP*) is 10.36, the median value of *GDP Growth* is 6.3%, and the median score for legal environment (*LEG_ENV*) is 3.039.

Panel B of Table 2 provides annual CRI scores by continent.[17] They vary over time. For example, in the case of Asia the highest score (−25.80) is in year 2006 and the lowest (−57.30) in year 2012. The mean values for Asia, North America, Oceania, Africa, Latin America, and Europe are −44.37, −52.86, −36.85, −51.91, −57.82, and −62.42 and their standard deviations are 9.95, 9.67, 14.60, 13.20, 18.61, and 8.49, respectively.

Panel C of Table 2 provides the Pearson correlations between climate risk and our measures of financial performance, earnings and cash flow volatility, and financing policies. Both annual and long-term climate risk measures are negatively and significantly related to ROA, CFO, short-term debt, and cash dividends and positively related to earnings volatility, operating cash flow volatility, long-term debt, short- and long-term debt, and cash holdings. These univariate correlations are consistent with our hypotheses.

Table 2 Descriptive statistics and correlation for variables

Panel A: Descriptive statistics

Variables	Mean	SD	P25	Median	P75	No. of countries	No. of obs.
Climate Risk (Annual)	−44.53	25.11	−63.50	−38.00	−25.17	55	147,223
Climate Risk (Long term)	−65.59	31.21	−92.00	−48.00	−44.83	55	353,906
ROA	−0.005	0.212	−0.018	0.040	0.093	55	353,906
CFO	0.041	0.184	−0.003	0.061	0.127	55	326,087
Earnings Volatility	0.045	0.072	0.010	0.020	0.045	55	218,763
Operating Cash Flow Volatility	0.071	0.075	0.026	0.048	0.085	55	214,647
Short-term Debt	0.111	0.144	0.004	0.052	0.163	55	353,752
Long-term Debt	0.152	0.198	0.001	0.076	0.227	55	353,828
Short and LONG-term Debt	0.272	0.273	0.049	0.214	0.399	55	353,452
Cash Holdings	0.482	1.420	0.034	0.104	0.277	55	351,895
Cash Dividends	0.018	0.031	0.000	0.006	0.021	55	261,581
SIZE	6.532	2.935	4.372	6.280	8.486	55	353,906
Total Debt	0.625	0.411	0.365	0.569	0.774	55	353,906
Ln(age)	2.150	0.729	1.609	2.197	2.639	55	353,906
Intangible Assets	0.100	0.184	0.000	0.011	0.105	55	353,906
PPE	0.346	0.286	0.122	0.281	0.492	55	353,906
Sales Growth	0.188	0.574	−0.041	0.075	0.248	55	353,906
LGDP	9.725	1.339	9.121	10.360	10.590	55	353,906
GDP Growth	0.069	0.094	0.033	0.063	0.115	55	353,906
LEG_ENV	2.834	1.323	2.111	3.039	4.279	55	353,906

Panel B: Climate risk index by continent and year (2006–2012)

Year	Asia	North America	Oceania	Africa	Latin America	Europe
2006	−25.80	−40.55	−39.28	−63.98	−67.12	−51.72
2007	−52.81	−66.29	−41.25	−46.32	−74.45	−65.63
2008	−40.93	−53.24	−32.90	−22.97	−36.21	−60.70
2009	−44.15	−54.29	−17.04	−55.13	−55.77	−52.29
2010	−51.79	−61.07	−34.51	−56.64	−52.89	−65.76
2011	−37.83	−37.52	−25.65	−64.94	−31.16	−62.20
2012	−57.30	−57.05	−67.30	−53.37	−87.13	−78.63
Mean	−44.37	−52.86	−36.85	−51.91	−57.82	−62.42
SD	9.95	9.67	14.60	13.20	18.63	8.49

Panel C: Pearson correlation

		A	B	C	D	E	F	G	H	I	J	K
Climate Risk (Annual)	A	1										
Climate Risk (Long term)	B	0.699	1									
ROA	C	−0.034	−0.047	1								
CFO	D	−0.024	−0.044	0.647	1							
Earnings Volatility	E	0.046	0.025	−0.470	−0.414	1						
Operating Cash Flow Volatility	F	0.053	0.019	−0.302	−0.326	0.480	1					
Short-term Debt	G	−0.007	−0.029	−0.079	−0.103	0.062	0.067	1				
Long-term Debt	H	0.072	0.079	−0.012	0.016	−0.031	−0.105	0.043	1			
Short and Long-term Debt	I	0.054	0.043	−0.072	−0.048	0.033	−0.031	0.617	0.779	1		
Cash Holdings	J	0.041	0.030	−0.295	−0.360	0.262	0.181	−0.126	−0.096	−0.134	1	
Cash Dividends	K	−0.106	−0.069	0.293	0.294	−0.123	−0.005	0.017	−0.070	−0.018	−0.062	1

Note: All correlations are significant at the $p < 0.05$ level.

MAIN RESULTS

Effect of Climate Risk on Financial Performance

Table 3 presents the test results relating to the effect of climate risk on financial performance. The sample includes the 55 countries listed in Table 1. Columns (1) and (2) show the results using the annual climate risk score with return-on-asset (*ROA*) and cash flow from operation (*CFO*) as the dependent variables. In both columns, we find the coefficients of the annual climate risk score to be significantly negative, indicating that higher climate risk is significantly associated with worse firm performance.[18] For example, in Column (1), the non-transformed coefficient (i.e., all coefficients in Tables 3, 4, and 5 have been multiplied by 100 for exposition purposes) of the annual climate risk is −0.00047 ($p < 0.000$), with the 95% confidence interval of between −0.00053 and −0.00040.[19] This

Table 3 Climate risk and firm performance

	(1) ROA	(2) CFO	(3) ROA	(4) CFO
Climate Risk (Annual)	−0.047	−0.030		
	(0.003)	(0.003)		
Climate Risk (Long term)			−0.009	−0.008
			(0.002)	(0.002)
SIZE	0.021	0.014	0.020	0.015
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(age)	0.009	0.012	0.013	0.018
	(0.001)	(0.001)	(0.001)	(0.001)
Intangible Assets	0.119	0.122	0.110	0.097
	(0.005)	(0.005)	(0.004)	(0.004)
PPE	0.092	0.120	0.099	0.121
	(0.003)	(0.003)	(0.003)	(0.003)
Total Debt	−0.094	−0.063	−0.089	−0.059
	(0.003)	(0.003)	(0.002)	(0.002)
Sales Growth	0.028	−0.007	0.016	−0.021
	(0.002)	(0.002)	(0.001)	(0.001)
LGDP	−0.021	−0.014	−0.013	−0.004
	(0.001)	(0.001)	(0.001)	(0.001)
GDP Growth	0.055	−0.019	0.068	0.016
	(0.008)	(0.007)	(0.005)	(0.005)
LEG_ENV	0.002	0.008	−0.006	−0.004
	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	0.055	0.009	0.029	−0.033
	(0.011)	(0.010)	(0.008)	(0.007)
Industry/year	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes
No. of observations	147,223	145,749	353,906	326,087
Adjusted R^2	0.209	0.165	0.182	0.158
F	120.3	98.49	162.6	135.2
No. of countries	55	55	55	55

This table presents the regression results of the impact of climate risk on financial performance. Regressions include year and industry fixed effects. The standard errors reported in parentheses are heteroskedasticity robust and clustered at the firm level. To conserve space, we do not report the coefficient estimates for the industry and year dummies. For exposition purposes, we multiply the coefficients on climate risk by 100. All variables are defined in the Appendix.

indicates that moving from the first quartile (−63.50) to the third quartile (−25.17) of the annual climate risk score can reduce a firm's *ROA* by 1.8 percentage points.[20] The effect size of the annual climate risk is 0.0027, with the 95% confidence interval of between 0.0022 and 0.0032.[21]

Similarly, in Column (2), the coefficient on the annual climate risk is −0.00030 ($p < 0.000$), with the 95% confidence interval of between −0.00036 and −0.00025. Moving from the first quartile (−63.50) to the third quartile (−25.17) of the annual climate risk score reduces a firm's *CFO* by 1.15 percentage points.[22] The effect size of the annual climate risk is 0.0015, with the 95% confidence interval of between 0.0011 and 0.0019. Columns (3) and (4) show similar results when using long-term climate risk as both coefficients are significantly negative. In sum, consistent with Hypothesis 1, Table 3 shows that higher climate risk can have significantly negative economic consequences on firm performance.

Effect of Climate Risk on Earnings Volatility

Table 4 shows the results of estimating the relationship between climate risk and earnings volatility. As we do not have the data necessary to calculate earnings volatility for Ecuadorian firms, the sample consists of 54 countries.[23] Columns (1) and (2) show the results for the annual climate risk and Columns (3) and (4) for the long-term climate risk. Results in Columns (1) and (2) indicate that the coefficients for the annual climate risk are significantly positive for accounting earnings volatility (coefficient = 0.0005 and $p < 0.000$) and

Table 4 Climate risk and earnings volatility

	(1) *Earnings Volatility*	(2) *Operating Cash Flow Volatility*	(3) *Earnings Volatility*	(4) *Operating Cash Flow Volatility*
Climate Risk (Annual)	0.005	0.016		
	(0.001)	(0.001)		
Climate Risk (Long term)			0.001	0.004
			(0.001)	(0.001)
ROA	−0.098		−0.103	
	(0.002)		(0.001)	
CFO		−0.079		−0.075
		(0.003)		(0.002)
SIZE	−0.005	−0.007	−0.006	−0.008
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(age)	−0.004	−0.005	−0.005	−0.002
	(0.001)	(0.001)	(0.000)	(0.000)
Intangible Assets	−0.013	−0.030	−0.010	−0.030
	(0.002)	(0.002)	(0.001)	(0.002)
PPE	−0.017	−0.027	−0.015	−0.026
	(0.001)	(0.002)	(0.001)	(0.001)
Total Debt	0.028	0.024	0.027	0.025
	(0.001)	(0.001)	(0.001)	(0.001)
Sales Growth	0.012	0.010	0.014	0.009
	(0.001)	(0.001)	(0.000)	(0.000)
LGDP	−0.002	−0.004	−0.001	−0.003
	(0.000)	(0.000)	(0.000)	(0.000)
GDP Growth	0.014	0.031	0.028	0.047
	(0.003)	(0.003)	(0.003)	(0.003)
LEG_ENV	0.004	−0.002	0.005	−0.002
	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.081	0.166	0.058	0.144
	(0.005)	(0.006)	(0.003)	(0.005)
Industry/year	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes
No. of observations	117,014	115,170	218,763	212,439
Adjusted R^2	0.278	0.197	0.310	0.203
F	110.3	88.79	203.3	113.6
No. of countries	54	54	54	54

This table presents the regression results of the impact of climate risk on performance volatility. Regressions include year and industry fixed effects. The standard errors reported in parentheses are heteroskedasticity robust and clustered at the firm level. To conserve space, we do not report the coefficient estimates for the industry and year dummies. For exposition purposes, we multiply the coefficients on climate risk by 100. All variables are defined in the Appendix.

operating cash flow volatility (coefficient = 0.00016 and $p < 0.000$). The 95% confidence interval of the coefficient is between 0.00026 (0.00013) and 0.00069 (0.00018), when the dependent variable is earnings volatility (operating cash flow volatility). The effect size of annual climate risk is 0.0003 (0.0026), with the 95% confidence interval of between 0.0001(0.0020) and 0.0005 (0.0032), when the dependent variable is earnings volatility (operating cash flow volatility).

Results in Columns (3) and (4) show that long-term climate risk has an insignificantly positive coefficient for earnings volatility but a significantly positive coefficient for operating cash flow volatility.[24] In sum, consistent with Hypothesis 1, Table 4 indicates that higher climate risk is associated with greater earnings volatility and operating cash flow volatility, consistent with extreme weather events disrupting normal operations.

Effect of Climate Risk on Financing Policies

Table 5 presents the results of our tests of the relationship between climate risk and a firm's policies on short-term and long-term debt, cash holding, and cash dividends. Panel A uses annual climate risk and Panel B long-term climate risk. In

Table 5 Climate risk and financial policy

Panel A: Climate risk (Annual) and financial policy

	(1) *Short-term Debt*	(2) *Long-term Debt*	(3) *Short and Long-term Debt*	(4) *Cash Holdings*	(5) *Cash Dividends*
Climate Risk (Annual)	−0.059	0.075	0.013	0.364	−0.020
	(0.003)	(0.003)	(0.004)	(0.026)	(0.001)
ROA	−0.127	−0.107	−0.273	−1.703	0.060
	(0.003)	(0.005)	(0.007)	(0.050)	(0.001)
SIZE	0.003	0.008	0.011	−0.037	−0.001
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
Ln(age)	−0.012	0.004	−0.007	−0.175	−0.002
	(0.001)	(0.001)	(0.002)	(0.010)	(0.000)
Intangible Assets	0.050	0.266	0.364	−0.385	0.010
	(0.004)	(0.006)	(0.007)	(0.036)	(0.001)
PPE	0.087	0.243	0.371	−0.159	0.006
	(0.003)	(0.005)	(0.006)	(0.034)	(0.001)
Leverage				−0.469	0.005
				(0.020)	(0.001)
Sales Growth	0.013	0.013	0.029	0.122	−0.002
	(0.001)	(0.001)	(0.002)	(0.014)	(0.000)
LGDP	−0.029	0.013	−0.019	0.150	−0.003
	(0.001)	(0.001)	(0.002)	(0.009)	(0.000)
GDP Growth	0.040	−0.085	−0.048	1.180	0.033
	(0.006)	(0.006)	(0.009)	(0.061)	(0.002)
LEG_ENV	0.009	−0.012	−0.001	−0.059	0.001
	(0.001)	(0.001)	(0.001)	(0.007)	(0.000)
Intercept	0.322	−0.110	0.216	0.248	0.046
	(0.012)	(0.014)	(0.020)	(0.094)	(0.003)
Industry/year	Yes	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes
No. of observations	147,183	147,202	147,029	146,156	107,824
Adjusted R^2/Pseudo R^2	0.156	0.239	0.263	0.298	0.177
F/χ^2	132.7	150.2	219.9	77.01	97.92
No. of countries	55	55	55	55	55

Panel B: Climate risk (Long term) and financial policy

	(1) *Short-term Debt*	(2) *Long-term Debt*	(3) *Short and Long-term Debt*	(4) *Cash Holdings*	(5) *Cash Dividends*
Climate Risk (Long term)	−0.040	0.063	0.016	0.115	−0.010
	(0.002)	(0.002)	(0.003)	(0.016)	(0.001)
ROA	−0.128	−0.084	−0.250	−1.491	0.039
	(0.002)	(0.003)	(0.005)	(0.031)	(0.001)
SIZE	0.005	0.006	0.012	−0.025	−0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Ln(age)	−0.008	0.010	0.002	−0.166	−0.001
	(0.001)	(0.001)	(0.001)	(0.006)	(0.000)
Intangible Assets	0.059	0.275	0.389	−0.296	0.009
	(0.003)	(0.005)	(0.006)	(0.025)	(0.001)
PPE	0.084	0.246	0.379	−0.076	0.008
	(0.003)	(0.004)	(0.004)	(0.022)	(0.001)
Leverage				−0.405	0.003
				(0.013)	(0.000)
Sales Growth	0.010	0.012	0.022	0.181	−0.002
	(0.001)	(0.001)	(0.001)	(0.009)	(0.000)
LGDP	−0.027	0.012	−0.017	0.093	−0.003
	(0.001)	(0.001)	(0.001)	(0.005)	(0.000)

Table 5 (*Continued*)

Panel B: Climate risk (Long term) and financial policy					
	(1) *Short-term Debt*	(2) *Long-term Debt*	(3) *Short and Long-term Debt*	(4) *Cash Holdings*	(5) *Cash Dividends*
GDP Growth	0.003	−0.016	−0.016	0.595	0.023
	(0.004)	(0.004)	(0.006)	(0.033)	(0.001)
LEG_ENV	0.007	−0.005	0.005	−0.008	0.000
	(0.001)	(0.001)	(0.001)	(0.005)	(0.000)
Intercept	0.270	−0.080	0.184	0.318	0.036
	(0.009)	(0.011)	(0.016)	(0.082)	(0.002)
Industry/year	Yes	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes
No. of observations	353,752	353,828	353,452	351,895	261581
Adjusted R^2/Pseudo R^2	0.141	0.232	0.261	0.234	0.156
F/χ^2	157.0	201.5	314.3	94.86	126.2
No. of countries	55	55	55	55	55

This table presents the regression results of the impact of climate risk on financial volatility. Regressions include the year and industry fixed effects. The standard errors reported in parentheses are heteroskedasticity robust and clustered at the firm level. To conserve space, we do not report the coefficient estimates for the industry and year dummies. For exposition purposes, we multiply the coefficients on climate risk by 100. All variables are defined in the Appendix.

Panel A, Column (1) indicates that annual climate risk is negatively associated with *Short-term Debt* (coefficient = -0.00059, $p < 0.000$), with the 95% confidence interval of between −0.00064 and −0.00054. The effect size of annual climate risk is 0.0083, with the 95% confidence interval of between 0.0074 and 0.0092.

Columns (2) and (3), on the other hand, show that annual climate risk is positively associated with both *Long-term Debt* and *Short- and Long-term Debt*.[25] In Panel B, Columns (1), (2), and (3) show similar results for long-term climate risk. In sum, consistent with Hypotheses 2 and 3, we find climate risk to be associated with higher long-term but lower short-term debt.

In Panel A of Table 5, Columns (4) and (5) show that annual climate risk is positively associated with cash holding and negatively associated with cash dividends. The results have economic significance. For example, in Column (4), the coefficient of 0.00364 on the annual climate risk indicates that moving from the first quartile (−63.5) to the third quartile (−25.17) of the annual climate risk score can increase a firm's cash holding by 13.95% of its total assets.[26] Similarly, in Column (5), the coefficient of −0.0002 for annual climate risk indicates that moving from the first quartile (−63.5) to the third quartile (−25.17) of the annual climate risk score can decrease a firm's cash dividend by 0.77% of its total assets.[27] The results in Columns (4) and (5) in Panel B also show that long-term climate risk is also positively associated with cash holding and negatively with cash dividends.[28] These results are consistent with Hypotheses 4 and 5.[29]

Overall, the evidence relayed in Table 5 suggests that firms in countries with higher climate risk borrow less short-term and more long-term, hold more cash, and issue lower cash dividends. This is consistent with using extra cash holding to mitigate cash flow volatility that may result from extreme weather events.

Effects of Vulnerable Industries

Different industries have different levels of vulnerability to extreme weather conditions. Climate risk can adversely affect firm profitability in at least two ways. First, extreme weather can inflict physical damage on assets and deprive a firm of potential revenue (Reisch, 2005). According to the Sustainability Accounting Standards Board (2016), Wilbanks et al. (2007), and McCarthy, Canziani, Leary, Dokken, and White (2001), industries with heavy non-deployed and long-lived capital assets are especially vulnerable to these kinds of loss. Industries of this kind include communications, energy (e.g., mining and oil extraction), healthcare, and utilities. Second, extreme weather can disrupt normal operations and lead to operating losses. The SASB (2016) and Wilbanks et al. (2007) show that industries dependent on moderate weather, with both an extended supply chain and a reliance on infrastructure, are likely to see their operations disrupted by extreme climate. Examples of these kinds of industries are agriculture and food

Table 6 Climate risk and vulnerable industries

	(1) *ROA*	(2) *CFO*	(3) *Earnings Volatility*	(4) *Operating Cash Flow Volatility*	(5) *Short-term Debt*	(6) *Long-term Debt*	(7) *Short and Long-term Debt*	(8) *Cash Holdings*	(9) *Cash Dividends*
Climate Risk (Annual)	−0.066	−0.047	0.004	0.012	−0.072	0.053	−0.018	0.294	−0.018
	(0.004)	(0.003)	(0.000)	(0.001)	(0.002)	(0.004)	(0.003)	(0.026)	(0.001)
Vulnerable Industries	−0.007	0.022	0.006	0.003	−0.034	−0.005	−0.039	0.281	0.001
	(0.004)	(0.004)	(0.000)	(0.001)	(0.002)	(0.004)	(0.003)	(0.152)	(0.001)
Climate Risk (Annual) × *Vulnerable Industries*	−0.021	−0.002	0.002	0.002	−0.017	0.030	0.014	0.351	−0.004
	(0.008)	(0.007)	(0.001)	(0.002)	(0.005)	(0.008)	(0.007)	(0.059)	(0.002)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry/year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	147,223	145,749	117,014	115,170	147,008	147,202	147,029	146,156	107,824
Adjusted R^2/Pseudo R^2	0.172	0.128	0.322	0.160	0.120	0.212	0.232	0.299	0.159
F/χ^2	312.7	234.8	2925	348.3	797.9	360.7	1542	75.82	271.6

This table presents the regression results of the impact of climate risk on vulnerable industries. *Vulnerable Industries* is an indicator variable that equals one for Agriculture (Fama–French Industry Code 1), Business Services (Code 34), Communication (Code 32), Energy [Mines (Code 28), Coal (Code 29), and Oil (Code 30)], Food Products (Code 2), Health Care (Code 11), and Transportation (Code 40), and zero otherwise. Regressions include the year fixed effects. The standard errors reported in parentheses are heteroskedasticity robust and clustered at the firm level. To conserve space, we do not report the coefficient estimates for the industry and year dummies. For exposition purposes, we multiply the coefficients on climate risk by 100. All variables are defined in the Appendix.

manufacturing that depend on land, water, and sun, and industries that provide business services and transportation. There is also support for this view from Fleming, Kirby, and Ostdiek (2006), Hsiang (2010), and Challinor, Watson, Lobell, Howden, Smith, and Chhetri (2014). Based on that literature, we consider agriculture, energy (including mining and oil extraction), food products, healthcare, communications, business services, and transportation to be vulnerable industries.[30] *Vulnerable industries* are coded one.

We include the interaction term *Climate Risk (Annual)* × *Vulnerable Industries* in Eq. (1) and present the regression results in Table 6. Columns (1), (3), (5), (6), (7), (8), and (9) show that the coefficients are generally significant and take the expected sign. Overall, this indicates that the adverse effect of climate risk on reducing ROA, increasing earnings volatility, borrowing less short-term but more long-term, and reducing cash dividends is more pronounced for these vulnerable industries. This industry-specific result provides additional supporting evidence for the link between climate risk and financial performance and financing policies.

ROBUSTNESS TESTS

Instrument Variable Method: Population Density

Because some of the country-level and firm-level variables are difficult to quantify and control, we used an instrumental variable method to re-estimate our models. In that robustness test, we chose population density as the instrumental variable because it is likely to be highly correlated with climate risk (Albouy, Graf, Kellogg, & Wolff 2013), but unlikely to be correlated with our dependent variables. We define *Population Density* as the number of people per square kilometer. We obtained country-year-level data from the World Bank. In the first stage, we regressed *Climate Risk (Long term)* on *Population Density* and on the firm-level control variables included in Eq. (1): *SIZE*, *Ln(age)*, *Intangible Assets*, *PPE*, and *Sales Growth*. We then computed the fitted value of *Climate Risk (Long term)* and included it in our second-stage regression based on Eq. (1). Panel A of Table 7 reports the first-stage results. As predicted, the coefficient of *Population Density* is negative and significant ($p < 0.000$), indicating a significantly negative association between population density and climate risk. Panel B of Table 6 shows that including fitted

Table 7 Climate risk on firm performance and financing choices: Instrument variable method

Panel A: First stage to estimate fitted value of climate risk

	(1) *Climate Risk (Long term)*
Population Density	−0.167
	(0.000)
SIZE	−0.020
	(0.000)
Ln(age)	0.026
	(0.002)
Intangible Assets	0.010
	(0.006)
PPE	0.021
	(0.005)
Sales Growth	0.019
	(0.001)
Intercept	−0.542
	(0.016)
Industry/year	Yes
No. of observations	353,906
Pseudo R^2	0.394

Panel B: Climate risk and firm performance

	(1) *Earnings Volatility*	(2) *Operating Cash Flow Volatility*	(3) *Earnings Volatility*	(4) *Operating Cash Flow Volatility*
Fitted Climate Risk (Long term)	−0.056	−0.032	0.006	0.004
	(0.003)	(0.003)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
No. of observations	353,906	326,087	218,763	212,439
Adjusted R^2	0.184	0.159	0.310	0.203

Panel C: Climate risk and financial policy

	(1) *Short-term Debt*	(2) *Long-term Debt*	(3) *Short and Long-term Debt*	(4) *Cash Holdings*	(5) *Cash Dividends*
Fitted Climate Risk (Long term)	−0.043	0.036	−0.011	0.026	−0.009
	(0.003)	(0.003)	(0.005)	(0.022)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes
No. of observations	353,752	353,828	353,452	351,895	261,581
Adjusted R^2/Pseudo R^2	0.149	0.245	0.263	0.236	0.152

This table presents the OLS estimation results relating climate risk to firm performance and financial policy using instrument variable method. Panel A presents the first-stage OLS model estimation results. Specifically, the dependent variable in the first stage is *Climate Risk (Long term)*. *Population Density* is the number of people (in 1000) per squared kilometer of land area, and Panels B and C report OLS results of examining the relation between the fitted value of *Climate Risk (Long term)* on firm performance and financing choices, respectively. The standard errors reported in parentheses are heteroskedasticity robust and clustered at the firm level. To conserve space, we do not report the coefficient estimates for the industry and year dummies. For exposition purposes, we multiply the coefficients on climate risk by 100. All variables are defined in the Appendix.

Climate Risk (Long term) in the second-stage regression does not change our results, and hence that they are unlikely to be driven by omitted country-level variables.

Propensity-Score-Matched Sample

In a second robustness test, we used a propensity-score-matched sample to address the concern, the results of which may be driven by differences in firm characteristics between high-climate risk and low-climate risk groups (Ghoul, Guedhami, & Kim, 2017).[31] We define *High Climate Risk* as firm-year climate risk above the sample median. In the first stage, we regressed our *High Climate Risk* dummy on the firm-level control variables included in Eq. (1): *SIZE*, *Ln(age)*, *Intangible Asset*, *PPE*, and *Sales Growth*. Panel A of Table 8 reports the regression results. We then computed the propensity score for each

Table 8 Climate risk on firm performance and financing choices: propensity score matching

Panel A: First-stage propensity score matching

	(1) *High Climate Risk*
SIZE	0.068
	(0.003)
Ln(age)	0.579
	(0.010)
Intangible Assets	−0.118
	(0.034)
PPE	−0.414
	(0.027)
Sales Growth	0.219
	(0.014)
Intercept	1.734
	(0.119)
Industry/year	Yes
No. of observations	167,234
Pseudo R^2	0.143

Panel B: Climate risk and firm performance

	(1) *Earnings Volatility*	(2) *Operating Cash Flow Volatility*	(3) *Earnings Volatility*	(4) *Operating Cash Flow Volatility*
High Climate Risk	−0.014	−0.012	0.001	0.003
	(0.003)	(0.002)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
No. of observations	74,372	74,372	74,372	74,372
Adjusted R^2	0.227	0.185	0.290	0.158

Panel C: Climate risk and financial policy

	(1) *Short-term Debt*	(2) *Long-term Debt*	(3) *Short and Long-term Debt*	(4) *Cash Holdings*	(5) *Cash Dividends*
High Climate Risk	−0.009	0.050	0.040	0.035	−0.008
	(0.002)	(0.003)	(0.004)	(0.017)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes
No. of observations	74,372	74,372	74,372	74,372	74,372
Adjusted R^2/Pseudo R^2	0.165	0.287	0.281	0.170	0.172

This table presents the OLS estimation results relating climate risk to firm performance and financial policy using propensity score matching method. Panel A presents the first-stage Probit model estimation results. Specifically, the dependent variable in the first stage is *High Climate Risk*, an indicator variable that equals one if *Climate Risk (Long term)* is above sample median, and zero otherwise. We regress *High Climate Risk* on firm characteristics and use the estimated coefficients from this first-stage model to compute the propensity score for each observation in our sample. We then match each firm-year that in the high-climate risk group with a firm-year in the low-climate risk group, with the closest propensity score. Panel B reports OLS results of examining the relation between climate risk on firm performance and financing choices, using propensity-score-matched sample. The standard errors reported in parentheses are heteroskedasticity robust and clustered at the firm level. To conserve space, we do not report the coefficient estimates for the industry and year dummies. For exposition purposes, we multiply the coefficients on climate risk by 100. All variables are defined in the Appendix.

observation in our sample. We matched each firm-year in the high-climate risk group with the firm-year in the low-climate risk group with the closest propensity score. Panel B of Table 8 reports the OLS estimation result of the relationship between climate risk, financial performance, and financing choices using the matched sample under Eq. (1). The results are unchanged.

Insurance Coverage

We used country-level growth in non-life insurance payments as a proxy for country-level insurance coverage (*Insurance*). The data come from Global Insurance Market Trends. In unreported results, we find that the level of insurance coverage is higher for countries with higher climate risk. We then tested whether insurance coverage can mitigate adverse effects of climate risk on firm performance and earnings volatility by interacting country-level insurance coverage with CRI. We find significantly positive coefficients for *ROA* and *CFO* and negative ones for *Earnings Volatility* and *Operating Cash Flow Volatility*. This suggests that insurance coverage can mitigate the adverse effect of climate risk on firm performance and earnings volatility.[32]

CRI for US Multinational Firms

Given the ability of multinational firms to move their operations out of high-climate risk areas, we adjusted the CRI based on the countries where a given multinational is active. Lack of national sales data and segment data for multinationals not headquartered in the US limited somewhat our ability to test firm sensitivity to climate risk. As an alternative approach, we obtained from the Compustat segments database US multinational firm revenue for specific geographic areas. We merged those data with country-year-level CRI and computed the arithmetic average CRI for each firm weighted by its revenue from different countries. We attempted to replicate the previous regressions using this weighted *CRI*. Consistent with our previous results, we find in unreported results a negative impact from climate risk on operating performance measured as CFO and the same impact on financing decisions that we reported earlier.

Alternative Measure of Global Climate Risk

To provide a robustness test for our measure of climate risk, we used another measure of global climate risk. We obtained the Global Climate Report from the National Oceanic and Atmospheric Administration (NOAA) website.[33] The Global Climate Report has included since 2009 a Significant Climate Anomalies and Events section. Based on these data, we created a dummy variable (SCAE), which equals one if a country suffers one or more climatic anomalies or events, and zero otherwise. The variable is not based on the loss of GDP and thus is free of the influence of a country's economic development and performance. We replicated the previous tests using SCAE (instead of CRI). As shown in Table 9, the results continue to be robust, suggesting that they are not driven by GDP level or growth.

Other Robustness Tests

We conducted an array of additional robustness tests. The results, which are not reported, are similar. First, we excluded all US observations,

Table 9 Alternative measure of extreme climate risk – extreme climate events

	(1) *ROA*	(2) *CFO*	(3) *Earnings Volatility*	(4) *Operating Cash Flow Volatility*	(5) *Short-term Debt*	(6) *Long-term Debt*	(7) *Short and Long-term Debt*	(8) *Cash Holdings*	(9) *Cash Dividends*
SCAE	−0.007	−0.001	0.004	0.007	−0.030	0.036	0.004	0.168	−0.003
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.016)	(0.001)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry/year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	85,275	84,447	69,313	68,160	85,238	85,264	85,132	84,656	60,881
Adjusted R^2/Pseudo R^2	0.176	0.122	0.269	0.201	0.159	0.231	0.251	0.297	0.173
F/χ^2	330.6	230.2	75.34	73.73	106.4	121.2	156.3	59.49	63.84

This table presents the regression results of using an alternative measure of extreme climate risk – extreme climate event. SCAE refers to an indicator variable that equals one if a country suffers one or more significant climate anomalies or events, and zero otherwise. Source: Significant Climate Anomalies and Events, Global Climate Report from National Oceanic and Atmospheric Administration (NOAA). Regressions include the year fixed effects. The standard errors reported in parentheses are heteroskedasticity robust and clustered at the firm level. To conserve space, we do not report the coefficient estimates for the industry and year dummies. For exposition purposes, we multiply the coefficients on climate risk by 100. All variables are defined in the Appendix.

which constitute 27% of our sample (see Table 1), in order to check that the findings are not US driven. Second, following Edwards (1992), we used country-weighted least squares regression to control for the different weights of countries in the sample. Third, we ran the four indicators of climate risk one at a time (instead of combined). Fourth, we restructured the CRI giving equal weights to its four indicators. Fifth, while Goodwin and Wu (2014) suggest that controlling for country-level fixed effects will reduce the likelihood of observing significant results, we find that including them does not alter our conclusion that climate risk has a profound impact on important financing decisions. Sixth, we measured the climate risk index for the year prior to financial policies. Seventh, we defined the financial crisis period separately for each country based on GDP growth rate and find that the results are robust to either interacting financial crisis years with climate risk or dropping financial crisis years from the sample.[34]

CONCLUSION

Our work contributes to a growing literature on the impact of climate risk on firm decisions. It is one of the first cross-country studies of the direct impact of global climate risk on public firm policies and performance. We provide evidence that managers of public firms across the globe weigh the loss due to extreme weather-related events such as storms, floods, and heat waves, i.e., *climate risk*, when making financing choices. First, as expected, we find that climate risk is negatively associated with firm earnings and positively associated with earnings volatility. This implies that firms cannot fully offset climate risk by insuring against it, either because they are unwilling or unable to do so. We also show that the managers of firms in countries characterized by severe climate risk tend to hold more cash, rely less on short-term and more on long-term borrowing, and pay lower cash dividends. We find similar results using an instrumental variable approach, propensity score matching, path analysis, and an alternative measure of climate risk. Our results are consistent with firms creating financial slack in order to maintain 'organizational resilience' against the threat of climate risk. They are more pronounced in the case of industries that are more vulnerable to climate risk. Our conclusions are invariant to the timing of financial crises that can affect different countries at different times. The strategies documented in our article appear to be consistent with attempts by managers to mitigate the increased volatility and uncertainty of future earnings and cash flows caused by higher climate risk.

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NOTES

[1]According to United Nations International Strategy for Disaster Reduction (UNISDR, 2009), risk is the "combination of the probability [of occurrence] of a certain event and its negative consequences."

[2]A large part of the economic damage emanating from extreme weather events is not insured, especially in the case of developing countries (Andersen, 2001; Bals, Warner, & Butzengeiger, 2006). Catastrophic insurance usually covers only damage to the means of production (e.g., property), not indirect losses such as lost proceeds from property that is destroyed, not losses that other agents may suffer, e.g., loss of supplies from damaged property (Bals et al. 2006). Hence underlying our study is the assumption that firms cannot fully insure against climatic risk. To the extent that they can do so, we anticipate that our findings will be less significant.

[3]Bansal and Ochoa (2012) propose that equity returns in countries with higher temperatures (i.e., those closer to the Equator) have a positive temperature risk premium; they also show that increases in global temperature negatively affect the economic growth of countries closer to the Equator.

[4]Albouy et al. (2013) posit that US households prefer a certain temperature level and find a cost of living premium in areas with such levels.

[5]Concern about the effect of rising temperatures is growing. Pal and Eltahir (2016) predict that the temperature in Southwest Asia will rise beyond the habitable level if global warming is left unabated.

[6]Seasonal affective disorder refers to an extensively documented medical condition whereby the shortness of the daylight in fall and winter leads to greater depression and, in turn, heightened risk aversion.
[7]Prior literature tends to treat sunshine and temperature as two distinct weather variables. For example, Howarth and Hoffman (1984) show that skepticism is positively associated with temperature and negatively associated with the amount of sunshine.
[8]Interest in climate change has resulted in a recent strand of studies in this area including some that focus on the impact on firm valuation, as carbon dioxide emissions, hazardous chemicals, and other pollutants may result in onerous regulatory requirements, financial or reputational damage, or costly litigation. Konar and Cohen (2001) show that intangible asset valuation is negatively associated with levels of emitted toxic chemicals, Matsumura et al. (2014) that carbon emissions can negatively affect firm value, and Beatty and Shimshack (2010) that firms suffer from negative market returns when poorly rated on managing (i.e., measuring, reporting, and reducing) greenhouse gas emissions. Based on US evidence, Chava (2014) finds that investors charge firms with higher greenhouse emissions and hazardous chemical discharges more for equity and debt capital. Using a European sample, Tu (2014) finds that firms with better carbon management performance have better share performance. On the other hand, Anderson, Bolton, and Samama (2016) document that carbon risk is currently underpriced by financial markets and investors can hedge against climate risks without losing any returns. Finally, Clapp, Alfsen, Torvanger, and Lund (2015) argue that climate science should play a crucial role in verifying that the "green projects" of firms are climate friendly. However, these studies do not directly study the impact of climate events (as opposed to concerns) on firm valuation and decision-making.
[9]Atta-Mensah (2016) suggests that countries and firms can issue weather-linked bonds to hedge against volatility due to weather-dependent assets.
[10]Firms in larger countries can possibly move from a country's high-climate risk area to one where the risk is less. That possibility would tend to reduce the robustness of any findings. At the same time, many firms cannot relocate (e.g., some retailers and firms in communication and transportation).
[11]"Geological factors like earthquakes, volcanic eruptions and tsunamis, for which data is also available, are not included as they are not weather-related per se and therefore not climate change-related" (Kreft & Eckstein, 2014: 16).
[12]We were not able to obtain annual scores from the 2006 and 2007 editions.
[13]Economic losses comprise "all elementary loss events which have caused substantial damage to property or persons" or in other words, direct losses (Kreft & Eckstein, 2014: 16). Indirect losses, i.e., the losses that firms experience due to damaged assets and those of their customers, are not included. However, they are highly correlated to direct losses (Hallegatte, 2008; Kowalewski & Ujeyl, 2012).
[14]Because indicators 3 and 4, sum of losses in US$ at PPP and losses as a percent of GDP, are likely to be affected by the economic size and performance of a country, we control for level and change of GDP in our multivariate regression analysis. Also, according to Kreft and Eckstein (2014: 20), "the indicator 'absolute losses in US$' is identified by purchasing power parity (PPP), because using this figure better expresses how people are actually affected by the loss of one US$ than by using nominal exchange rates."
[15]One limitation of this study is that we do not account for how a firm might be affected by climate risk associated with its material operations located overseas.
[16]We winsorized all the continuous variables at the 1 and 99% levels.
[17]To save space, we do not provide the annual CRI by countries where the results are similar.
[18]Results not reported here indicate that both annual and long-term climate risk scores are positively associated with firms having negative extraordinary items and discontinued items.
[19]Meyer, Witteloostuijn, and Beugelsdijk (2017) point out that it is important to discuss the confidence interval of the coefficient. To save space, we do not provide the confidence intervals in the tables.
[20]It is calculated as follows: $(-25.17 - (-63.50)) \times (-0.00047) = -0.0108$.
[21]Effect size refers to the magnitude of the effects (Ferguson, 2009).
[22]It is calculated as follows: $(-25.17 - (-63.50)) \times (-0.0003) = -0.0115$.
[23]The quarterly pre-tax income (PI) of firms in Ecuador is not given. Thus, we are not able to calculate *Earnings Volatility* for Ecuador and so cannot include Ecuador in our sample, leading to the reduction of sample size from 55 countries in Table 3 to 54 countries in Table 4.
[24]Rountree et al. (2008) argue that investors are mainly concerned about the cash flow (as opposed to accounting) component of earnings volatility. Moreover, illiquidity issues are usually caused by cash flow volatility, not earnings volatility.

[25]The results indicate that these firms have higher long-term debt and total debt, which is a sign of financial distress (Banerjee, Dasgupta, & Kim, 2008) and can be a result of poor earnings performance resulting from extreme weather events.
[26]It is calculated as follows: $(-25.17 - (-63.5)) \times (0.00364) = 0.1395$.
[27]It is calculated as follows: $(-25.17 - (-63.5)) \times (-0.0002) = -0.0077$.
[28]Our results are robust to controlling for whether a country's company law or commercial code requires firms to distribute certain percentage of their income as dividends (La Porta et al., 1998).
[29]The results in Table 5 may be due to extreme weather or to volatility in higher earnings and cash holdings as suggested in Table 4. We use path analysis (e.g., Wright, 1934) to examine these potential dependencies where annual extreme weather is treated as the direct path and earnings volatility as the mediated (indirect) path. We find that both direct and mediated paths are significant and positive, indicating that the financing policies are affected by both organizational resilience and earnings volatility.
[30]We use the Fama–French Industry classification.
[31]Using propensity-score-matched sample is an effective method to address endogeneity issue in cross-country studies (e.g., Ghoul et al., 2017).
[32]Results are available from the authors.
[33]https://www.ncdc.noaa.gov/sotc/global.
[34]For convenience, we use a definition of a recession commonly used in the business press involving a fall in GDP for two successive quarters. [Note that the NBER defines a recession more broadly as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales" (NBER, 2008)].

REFERENCES

Albouy, D., Graf, W., Kellogg, R., & Wolff, H. 2013. Climate amenities, climate change, and American quality of life. Working Paper. Cambridge, MA: National Bureau of Economic Research.
Andersen, T. 2001. *Managing economic exposures of natural disasters: Exploring alternative financial risk management opportunities and instruments* (p. 2001). Washington, DC: Natural Disasters Dialogue First Meeting.
Anderson, M., Bolton, P., & Samama, F. 2016. Hedging climate risk. *Financial Analysts Journal,* 72(3): 13–32.
Atta-Mensah, J. 2016. Poverty, climate risk and weather-indexed bonds. *Journal of Mathematical Finance,* 6(2): 275–292.
Bals, C., Warner, K., & Butzengeiger, S. 2006. Insuring the uninsurable: Design options for a climate change funding mechanism. *Climate Policy,* 6(6): 637–647.
Banerjee, S., Dasgupta, S., & Kim, Y. 2008. Buyer–supplier relationships and the stakeholder theory of capital structure. *Journal of Finance,* 63(5): 2507–2552.
Bansal, R., & Ochoa, M. 2012. Temperature, aggregate risk, and expected returns. Unpublished Working Paper No. 17575. Cambridge, MA: National Bureau of Economic Research.
Bates, T., Kahle, K., & Stulz, R. 2009. Why do US firms hold so much more cash than they used to? *Journal of Finance,* 64(5): 1985–2021.
Beatty, T., & Shimshack, J. 2010. The impact of climate change information: New evidence from stock market. *Journal of Economic Analysis and Policy,* 10(1): 1–29.
Berkes, F., Colding, J., & Folke, C. (eds.). 2003. *Navigating social–ecological systems: Building resilience for complexity and change*. Cambridge: Cambridge University Press.
Berkhout, F., Hertin, J., & Gann, D. M. 2006. Learning to adapt: Organizational adaptation to climate change impacts. *Climatic Change,* 78(1): 135–156.
Burke, M., Hsiang, S. M., & Miguel, E. 2015. Global non-linear effect of temperature on economic production. *Nature,* 527(7577): 235–239.
Burnell, P. 2012. Democracy, democratization and climate change: Complex relationship. *Democratization,* 19(5): 813–842.
Cao, M., & Wei, J. 2005. Stock market returns: A note on temperature anomaly. *Journal of Banking & Finance,* 29(6): 1559–1573.
Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., & Chhetri, N. 2014. A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change,* 4(4): 287–291.
Chava, S. 2014. Environmental externalities and cost of capital. *Management Science,* 60(9): 2223–2247.
Clapp, C. S., Alfsen, K. H., Torvanger, A., & Lund, H. F. 2015. Influence of climate science on financial decisions. *Nature Climate Change,* 5(2): 84–85.
Covington, H., & Thamotheram. R. 2015. The case for forceful stewardship (part 1): The financial risk from global warming. Working Paper. Cambridge, MA: Cambridge University and University of Oxford.
Custodio, C., Ferreira, M., & Laureano, L. 2013. Why are US firms using more short-term debt? *Journal of Financial Economics,* 108(1): 182–212.
Dell, M., Jones, B., & Olken, B. A. 2009. Temperature and income: Reconciling new cross-sectional and panel estimates. *American Economic Review,* 99(2): 198–204.
Dell, M., Jones, B., & Olken, B. A. 2014. What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature,* 52(3): 740–798.
Deryugina, T. 2011. The role of transfer payments in mitigating shocks: Evidence from the impact of hurricanes. Working Paper. Champaign, IL: University of Illinois.
Diamond, D. 1991. Debt maturity structure and liquidity risk. *Quarterly Journal of Economics,* 106(3): 709–737.
Dichev, I., & Tang, V. 2009. Earnings volatility and earnings predictability. *Journal of Accounting and Economics,* 47(1): 160–181.
Djankov, S., McLiesh, C., & Shleifer, A. 2007. Private credit in 129 countries. *Journal of Financial Economics,* 84(2): 299–329.
Edwards, S. 1992. Trade orientation, distortions, and growth in developing countries. *Journal of Development Economics,* 39(1): 31–58.

Ferguson, C. J. 2009. An effect size primer: A guide for clinicians and researchers. *Professional Psychology,* 40(5): 532–538.
Fleming, J., Kirby, C., & Ostdiek, B. 2006. Information, trading, and volatility: Evidence from weather-sensitive markets. *The Journal of Finance,* 61(6): 2899–2930.
Francis, J., LaFond, R., Olsson, P. M., & Schipper, K. 2004. Costs of equity and earnings attributes. *The Accounting Review,* 79(4): 967–1010.
Fuss, S. 2016. Climate economics: Substantial risk for financial assets. *Nature Climate Change,* 6(7): 659–660.
Gallup, J., Sachs, J., & Mellinger, A. 1999. Geography and economic development. *International Regional Science Review,* 22(2): 179–232.
Garschagen, M., & Romero-Lankao, P. 2015. Exploring the relationships between urbanization trends and climate change vulnerability. *Climate Change,* 133(1): 37–52.
Ghoul, S. E., Guedhami, O., & Kim, Y. 2017. Country-level institutions, firm value, and the role of corporate social responsibility initiatives. *Journal of International Business Studies,* 48(3): 360–385.
Goodwin, J., & Wu, D. 2014. Is the effect of industry expertise on audit pricing an office-level or a partner-level phenomenon? *Review of Accounting Studies,* 19(4): 1532–1578.
Hallegatte, S. 2008. An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina. *Risk Analysis,* 28(3): 779–799.
Hirshleifer, D., & Shumway, T. 2003. Good day sunshine: Stock returns and the weather. *Journal of Finance,* 58(3): 1009–1032.
Hoffmann, V. H., Sprengel, D. C., Ziegler, A., Kolb, M., & Abegg, B. 2009. Determinants of corporate adaptation to climate change in winter tourism: An econometric analysis. *Global Environmental Change,* 19(2): 256–264.
Howarth, E., & Hoffman, M. S. 1984. A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology,* 75(1): 15–23.
Hsiang, S. M. 2010. Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National academy of Sciences of the United States of America,* 107(35): 15367–15372.
Hsiang, S. M., & Narita, D. 2012. Adaptation to cyclone risk: Evidence from the global cross-section. *Climate Change Economics,* 3(2): 1250011-1–1250011-28.
Huang, T., Wu, F., Yu, J., & Zhang, B. 2015. Political risk and dividend policy: Evidence from international political crises. *Journal of International Business Studies,* 46(5): 574–595.
IPCC. 2007. Climate change 2007: Synthesis Report, Fourth assessment report (AR4) of the Intergovernmental Panel on Climate Change (IPCC).
Itzkowitz, J. 2013. Customers and cash: How relationships affect suppliers' cash holdings. *Journal of Corporate Finance, 19,* 159–180.
Jahn, M. 2013. Economics of extreme weather events in cities: Terminology and regional impact models. HWWI research Paper 143, Hamburg Institute of International Economics.
Kamstra, M. J., Kramer, L. A., & Levi, M. D. 2003. Winterblues: A SAD stock market cycle. *American Economic Review,* 93(1): 324–343.
Kingsley, A. F., & Graham, B. A. 2017. The effects of information voids on capital flows in emerging markets. *Journal of International Business Studies,* 48(3): 324–343.
Konar, S., & Cohen, M. A. 2001. Does the market value environmental performance? *The Review of Economics and Statistics,* 83(2): 281–289.
Kowalewski, J., & Ujeyl, G. 2012. Estimating direct and indirect damages from storm surges: The case of Wilhelmsburg/Hamburg. In F. Klijn & T. Schweckendiek (Eds.), *Comprehensive flood risk management: Research for policy and practice.* Delft: CRC Press.
Kreft, S., & Eckstein, D. 2014. *Global climate risk index 2014*. Bonn: Germanwatch.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. 1998. Law and finance. *Journal of Political Economy,* 106(6): 1113–1155.
Larkin, K. 2013. Brand perception, cash flow stability, and financial policy. *Journal of Financial Economics,* 110(1): 232–253.
Le, S., & Kroll, M. 2017. CEO international experience: Effects on strategic change and firm performance. *Journal of International Business Studies,* 48(5): 573–595.
Linnenluecke, M. K., & Griffiths, A. 2010. Beyond adaption: Resilience for business in light of climate change and weather extremes. *Business & Society,* 49(3): 477–511.
Linnenluecke, M. K., Griffiths, A., & Winn, M. I. 2008. Organizational adaptation and resilience to extreme weather events. Paper presented at the Annual Meetings of the Academy of Management, Anaheim, CA (Recipient of the Carolyn Dexter Best International Paper Award)
Lipe, R. 1990. The relation between stock returns and accounting earnings given alternative information. *The Accounting Review,* 65(1): 49–71.
Marano, V., Tashman, P., & Kostova, T. 2017. Escaping the iron cage: Liabilities of origin and CSR reporting of emerging market multinational enterprises. *Journal of International Business Studies,* 48(3): 386–408.
Masulis, R., & Mobbs, S. 2014. Independent director incentives: Where do talented directors spend their limited time and energy? *Journal of Financial Economics,* 111(2): 406–429.
Matsumura, E., Prakash, R., & Vera-Munoz, S. 2014. Firm-value effects of carbon emissions and carbon disclosures. *The Accounting Review,* 89(2): 695–724.
McCarthy, J., Canziani, O., Leary, N., Dokken, D., & White, K. 2001. *Climate change 2001: Impacts, adaptation, and vulnerability: Contribution of Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change.* Cambridge: Cambridge University Press.
Meyer, K., Witteloostuijn, A., & Beugelsdijk, S. 2017. What's in a p? Reassessing best practices for conducting and reporting hypothesis-testing research. *Journal of International Business Studies,* 48(5): 535–551.
Minton, B., & Schrand, C. 1999. The impact of cash flow volatility on discretionary investment and the costs of debt and equity financing. *Journal of Financial Economics,* 54(3): 423–460.
National Bureau of Economic Research (NBER). 2008. The NBER's recession dating procedure. *National Bureau of Economic Research*. http://www.nber.org/cycles/jan08bcdc_memo.html.
Nordhaus, W. D. 2006. Geography and macroeconomics: New data and new findings. *Proceedings of the National academy of Sciences of the United States of America,* 103(10): 3510–3517.
Novy-Marx, R. 2014. Predicting anomaly performance with politics, the weather, global warming, sunspots, and the stars. *Journal of Financial Economics,* 112(2): 137–146.
Opler, T., Pinkowitz, L., Stulz, R., & Williamson, R. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics,* 52(1): 3–46.
Pal, J. S., & Eltahir, E. A. B. 2016. Future temperature in southwest Asia projected to exceed a threshold for human adaptability. *Nature Climate Change,* 6(2): 197–200.
Reisch, M. 2005. Katrina's impact: In hurricane's aftermath, chemical firms face higher costs and lower earnings. *Chemical & Engineering News,* 83(38): 8.
Rivera, C., & Wamsler, C. 2014. Integrating climate change adaptation, disaster risk reduction and urban planning: A review of Nicaraguan policies and regulations. *International Journal of Disaster Risk Reduction,* 7: 78–90.
Ronen, J., & Sadan, S. 1981. *Smoothing income numbers: objectives, means, and implications*. Boston, MA: Addison-Wesley Publishing.
Rountree, B., Weston, J., & Allayannis, G. 2008. Do investors value smooth performance? *Journal of Financial Economics,* 90(3): 237–251.

SASB (Sustainability Accounting Standards Board). 2016. Climate risk technical bulletin. https://www.eenews.net/assets/2016/10/20/document_cw_01.pdf.
Stulz, R. 1990. Managerial discretion and optimal financing policies. *Journal of Financial Economics*, 26(1): 3–27.
Tschakert, P., & Dietrich, K. 2010. Anticipatory learning for climate change adaptation and resilience. *Ecology and Society*, 15(2): 11.
Tu, D. 2014. Do the stock markets price climate change risks? Working Paper. Paris: HEC. http://www.vernimmen.net/ftp/DoStockMktsPriceClimateChangeRisks_Danni_TU.pdf.
United Nations International Strategy for Disaster Reduction (UNISDR). 2009. UNISDR Terminology on Disaster Risk Reduction, Geneva. http://www.unisdr.org/_les/7817UNISDRTerminologyEnglish.pdf.
Vogus, T., & Sutcliffe, K. 2007. Organizational resilience: Towards a theory and research agenda, *2007 IEEE International Conference on Systems, Man and Cybernetics*, Montreal, Quebec, pp. 3418–3422.
Wang, J. 2012. Do firms' relationships with principal customers/suppliers affect shareholders' income? *Journal of Corporate Finance*, 18: 860–878.
Wilbanks, T. J., Romero Lankao, P., Bao, M., Berkhout, F., Cairncross, S., Ceron, J.-P., et al., 2007. Industry, settlement and society. *Climate Change*, 357–390.
Woods, D. 2006. Essential characteristics of resilience. In E. Hollnagel, D. D. Woods, & N. Leveson (Eds.), *Resilience engineering: Concepts and precepts* (pp. 21–34). Burlington, VT: Ashgate.
Wright, S. 1934. The method of path coefficients. *Annals of Mathematical Statistics*, 5: 161–215.
Yang, D. 2008. Coping with disaster: The impact of hurricanes on international financial flows, 1970–2002. *The BE Journal of Economic Analysis & Policy*, 8(1): 1–43.

APPENDIX

See Table 10.

Table 10 Variable definitions

Variable	Definition
Climate risk index	
Climate Risk (Annual)	Annual Climate Risk Index from Germanwatch's 2008–2014 editions (for the years 2006–2012) scaled by (−1). Higher score indicates higher Climate risk in the year. Sources: Germanwatch
Climate Risk (Long term)	Accumulated Climate Risk Index from Germanwatch's 2014 edition (covering the years 1993–2012) scaled by (−1). Higher score indicates higher Climate risk from 1993 to 2012. Sources: Germanwatch
High Climate Risk	Indicator variable that equals one if a firm-year's *Climate Risk (Long term)* is higher than the sample median, and zero otherwise. Sources: Germanwatch
SCAE	Indicator variable that equals one if a country suffers one or more climate anomalies or events (SCAE), and 0 otherwise. Source: Significant Climate Anomalies and Events
Financial performance	
ROA	Pre-tax Income (PI) scaled by lagged assets (AT). Sources: Compustat
CFO	Cash flows from operations (OANCF) scaled by total assets. Sources: Compustat
Performance volatility	
Operating Cash Flow Volatility	Cash flow volatility, measured by the standard deviation of quarterly cash flows from operations (OANCF) scaled by total assets (AT) over the preceding five fiscal years. Sources: Compustat
Earnings Volatility	Earnings volatility, measured by the standard deviation of quarterly pre-tax income (PI) scaled by total assets (AT) over the preceding five fiscal years. Sources: Compustat
Financial policy	
Short-term Debt	Short-term debt (DLC), scaled by lagged assets (AT). Sources: Compustat
Long-term Debt	Long-term debt (DLTT), scaled by lagged assets (AT). Sources: Compustat
Short and Long-term Debt	The sum of short- and long-term debt, scaled by lagged assets (AT). Sources: Compustat
Total Debt	Total liability (LT), scaled by lagged assets (AT). Sources: Compustat
Cash Holdings	Cash and short-term investment (CHE), scaled by lagged assets (AT). Sources: Compustat
Cash Dividends	Cash dividends (DVPD), scaled by lagged assets (AT). Sources: Compustat
Country-level control variables	
COMMON	Indicator that equals one if the legal origin is common law, and zero otherwise. Sources: La Porta et al. (1998)
EarnVol	Country-level control variable for earnings volatility. Sources: Compustat

Table 10 (*Continued*)

Variable	Definition
Factor	Principal component of the country's legal tradition (common law versus code law), strength of investor rights, and ownership concentration as developed by La Porta et al. (1998); Legal tradition refers to the indictor variable (COMMON), which equals one if the legal origin is common law, and zero otherwise (La Porta et al., 1998). Investor Rights is measured by an index aggregating the shareholder rights labeled as "anti-director rights." The index is formed by adding 1 when (1) the country allows shareholders to mail their proxy vote to the firm, (2) shareholders are not required to deposit their shares prior to the general shareholders' meeting, (3) cumulative voting or proportional representation of minorities in the board of directors is allowed, (4) an oppressed minorities mechanism is in place, (5) the minimum percentage of share capital that entitles a shareholder to call for an extraordinary shareholders' meeting is less than or equal to 10% (the sample median), or (6) shareholders have preemptive rights that can be waived only by a shareholders' vote. The index ranges from zero to six (La Porta et al., 1998; Djankov et al., 2007). Ownership concentration refers to the average percentage of common shares owned by the three largest shareholders in the 10 largest non-financial, privately owned domestic firms in a given country (La Porta et al., 1998). Sources: La Porta et al. (1998) and Djankov et al. (2007)
GDP Growth	Annual growth of total GDP. Sources: International Financial Statistics (IFM)
LEG_ENV	Principal component extracted from COMMON, ENFORCE, and CR. COMMON refers to an indicator that equals one if the legal origin is common law, and zero otherwise. ENFORCE refers to the law enforcement index that ranges from 0 to 10, with higher values indicating greater law enforcement. CR refers to creditor rights, which is formed by adding (1) when the country imposes restrictions, such as creditors consent or minimum dividends to file for reorganization; (2) when secured creditors are able to gain possession of their security once the reorganization petition has been approved (no automatic stay); (3) when secured creditors are ranked first in the distribution of the proceeds that result from the disposition of the assets of a bankrupt firm; and (4) when the debtor does not retain the administration of its property pending the resolution of the reorganization. The index ranges from 0 to 4. Sources: La Porta et al. (1998), Djankov et al. (2007), Economic Freedom of the World
LGDP	Log of GDP per capita, in constant 2000 US dollars. Sources: World Bank
Population Density	People (in 1000) per sq. km of land area. Sources: World Bank
Firm-level control variables	
SIZE ($ million)	The natural logarithm of asset (AT) at the beginning of the year. Sources: Compustat
Total Debt	Total liability, scaled by lagged assets (AT). Sources: Compustat
Intangible Assets	Intangible assets (INTAN), scaled by lagged assets (AT). Sources: Compustat
PPE	Net property, plant, and equipment (PPENT) divided by lagged assets. Sources: Compustat
ROA	Pre-tax Income (PI) scaled by lagged assets (AT). Sources: Compustat
R&D	Research and development expenditures (XRD) scaled by lagged assets (AT). Sources: Compustat
Sales Growth	Sales (SALE) change computed scaled by sales in the last fiscal year. Sources: Compustat
Ln(age)	Natural logarithm of firm age, which is calculated starting from the first year the firm appeared in the Compustat database. Sources: Compustat
Interaction variables	
Vulnerable Industries	Indicator variable that equals one for Agriculture (Fama–French Industry Code 1), Business Services (Code 34), Communication (Code 32), Energy [Mines (code 28), Coal (Code 29), and Oil (Code 30)], Food Products (Code 2), Health Care (Code 11), and Transportation (Code 40), and zero otherwise. Sources: Compustat

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