Climate Change and Financial Market Crash

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Abstract

Using data over 1934-2023, we find that climate change, proxied by temperature shock, predicts equity market crashes in the coming one-, two, and three-year horizon. The estimates, albeit weak in statistical significance, are of considerable economic significance. A one-standard-deviation increase in the shock elevates the probability of an aggregate market crash within subsequent two years by more than 11%. There is seemingly asymmetry in the predictive relation – a shock in the top (bottom) 10 percentile increases (decreases) the market crash probability. The results hold at both the aggregate and the industry levels and are more pronounced at the industry level.

JEL Codes: G10, G17, Q51, Q54, C35

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1. Introduction

Climate change affects economic activity and human society profoundly (e.g., Stern, 2007; Nordhaus, 2010; Hsiang, Burke, and Miguel, 2013; Dell, Jones, and Olken, 2014). A stream of the climate economics/finance literature is delving into the effects of climate change on aggregate consumption and equity valuations. A climate shock not only immediately reduces consumption but also reduces future expected consumption growth (e.g., Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015; Bansal, Kiku, and Ochoa, 2019). In the spirit of the long-run risk model, Bansal, Kiku, and Ochoa (2019) argue that rising temperature affects future long-term growth and risk, aggregate wealth, current asset valuations, and current returns. Moreover, a climate shock, the extreme one in particular, brings substantial uncertainty about outcomes of business performance and reactions of financial markets to the shock (e.g., Barro 2006; Kruttli, Tran, and Watugala, 2023). On the other hand, thanks to the increasing awareness to climate issues, economic agents may proactively take actions to mitigate the adverse effects of climate change. Furthermore, as weather conditions affect individuals' mood, sentiment and behavior, climate change also influences investor activities and asset prices nontrivially (e.g., Saunders, 1993; Hirschleifer and Shumway, 2003; Kamstra, Kramer, and Levi, 2003). In a nutshell, whether and how climate change affects financial asset valuations and financial market performance remain elusive.

In this paper we investigate the relations between climate change and financial market crash. Specifically, we hypothesize that climate shock predicts financial market crashes in the subsequent one to three years. Our conjecture is based on both theoretical asset pricing models embedding climate risk and empirical evidence that climate change impacts long-run growth, risk, and investor sentiment.

In implementation, we follow the literature to calculate temperature shock and use it as a proxy for climate change (e.g., Dell, Jones and Olken, 2009 & 2012; Addoum, Ng and Ortiz-

Bobea, 2020 & 2023). We view a market crash to occur if the monthly index return in excess of the risk-free rate is lower than -20%. In similar spirits to Baron and Xiong (2017), we define three equity market crash indicators that are respectively equal to one if the monthly excess index return is less than -20% for any month within the subsequent one-, two-, and three-year horizon, and to zero otherwise. We then predict equity market crash with climate shock and conduct both linear probability model estimations and Probit model estimations using data over the 1934-2023 period.

Our baseline finding is that climate change is positively associated with aggregate market crashes in the subsequent one to three years. The estimates are somewhat weak in statistical significance but of considerable economic significance. Using the estimates obtained with the climate shock as the sole predictor, we infer that a one-standard-deviation increase in the shock heightens the aggregate market crash probability by about 26.9%, 23.1%, and 9.0% (relative to the average crash probability) in the one-, two-, and three-year horizon, respectively. Based on the estimates obtained after controlling for such usual equity premium predictors as dividend yield, term spread, default spread, and stock variance in the regressions, a one-standard-deviation increase in the shock elevates the probability of an aggregate market crash within the coming one- and two-year horizon by about 13.5% and 11.5%, respectively.

There exits striking asymmetry for the shock in the left and right tails to predict aggregate market crashes. If a climate shock exceeds the 90^{th} percentile threshold, the probability of an aggregate market crash increases by about 27%, 20%, and 8% relative to the average probability in the subsequent one-, two, and three-year horizon, respectively. In contrast, if a climate shock is below the 10^{th} percentile threshold, the probability of a market crash in the coming one-, two, and three-year horizon decreases by about 40%, 26%, and 11% relative to the average probability, respectively. This asymmetry shows that abnormally hot weather and abnormally cold weather affect the aggregate equity market crash risk in qualitatively opposite ways.

We proceed to assess the predictive relation between climate shock and industry market crashes and find similar results. That is, climate shock positively predicts industry market crashes in the coming one to three years. The estimates have much stronger statistical significance than the estimates for the aggregate level and continue to carry considerable economic significance. There also exists seemingly asymmetry in predicting industry market crashes with climate shock in the left tail versus climate shock in the right tail. A climate shock in the top (bottom) 10 percentile is associated with increased (reduced) likelihood of an industry market crash in the subsequent one to three years. Notably, compared to the aggregate-level estimates, the industry-level estimates are more pronounced, reflecting that the aggregate market is well diversified and tends to experience less crashes than industries.

Our study contributes to the climate finance literature. A significant part of the literature examines the impacts of climate change on asset prices and investor activities (see, e.g., Giglio, Kelly, and Stroebel (2021) for a survey of the literature). To our best knowledge, we are the first to assess the relation between climate change and financial market crashes. As financial market crashes unlikely lead to abnormal temperature, our results point to a causal effect of climate shock on financial market crises.

Our analysis demonstrates that climate shock predicts future market crashes with considerable economic significance. In developing early warning systems for financial crises, researchers and policy makers have used a few early indicators such as asset price growth and volatility, credit spreads, credit-default swap spread on banks, and growth of bank credit to GDP (e.g., Schularick and Taylor, 2012; Krishnamurthy and Muir, 2016; Baron and Xiong, 2017; Hennig, Iossifov, and Varghese, 2023). Our analysis adds to this line of study by suggesting abnormal temperature as another potential predictor for future financial crises.

Our results have implications for both practitioners and policy makers. Understanding climate change and its impacts on financial market crises is of considerable importance to the development of investment strategy and risk management. Our analysis also informs the optimal policy response to climate change, global warning in particular.

The remainder of the paper proceeds as follows. Section 2 describes data and variable construction. Section 3 explains the empirical method. Section 4 presents empirical results. Section 5 concludes.

2. Data and Variable Construction

The data consist of several types of variables, namely, climate shock, equity index returns, and various variables known to predict the equity premium.

Following earlier works, our study focuses on temperature shock as the proxy for climate change (see, e.g., Dell, Jones and Olken, 2009 & 2012; Addoum, Ng and Ortiz-Bobea, 2020 & 2023). From the U.S. National Ocean and Atmospheric Administration's (NOAA) National Centers for Environmental Information (NCEI), we obtain monthly average temperature for the contiguous U.S. (excluding Alaska and Hawaii) from January 1895 to December 2023. We construct the monthly US-wide temperature shock (*SHK*) as the US average temperature in a month minus its past 40-year average of the same month.[1]

Our study uses the S&P 500 index as a proxy for the US equity market. Stock returns are the continuously compounded returns on the S&P 500 index, including dividends. The risk-free rate is the Treasury Bill rate. In similar spirits to Baron and Xiong (2017), we respectively define a crash indicator for one, two, and three years ahead for the market index, which equals one if the monthly index return in excess of the risk-free rate is less than -20% for any month within the one-, two-, and three-year horizon, and zero otherwise.[2] We denote the total excess

[1] NCEI calculates anormal temperature for a month as the difference between the month's temperature and the average temperature in the same months over 1901-2000. To avoid the look-ahead bias, we stochastically detrend the rolling averages of historic temperature to construct the temperature shock in our analysis.

[2] In practice, markets are said in bear territory if the market declines by 20% or more off its recent high. We thus choose -20% as the threshold to define the market crash indicators. We also experiment with other cutoffs like -10%, -15%, -25%, -30% and obtain qualitatively similar results.

returns in the one-, two-, and three-year horizon by *r_1y*, *r_2y*, and *r_3y*, respectively, and the corresponding crash indicators are *D_1y*, *D_2y*, and *D_3y*. For our study at the disaggregate level, we use the returns on the 10 industry portfolios defined in Fama and French (1997). Similarly, for each industry we define three industry crash risk indicators if the monthly continuously compounded return of the industry in excess of the risk-free rate is less than -20% for any month within the one-, two-, and three-year horizon, and zero otherwise.

We use the following control variables that are known to predict the equity premium (e.g., Goyal and Welch, 2008): dividend yield, term spread, default spread and stock variance. Dividend yield (*DY*) is the log of the 12-month moving sums of dividends paid on the S&P 500 index minus the log of the one-period-lagged price level of the index. The term spread (*TMS*) is the difference between the ten-year Treasury bond yield and the Treasury bill yield. The default spread (*DEF*) is the yield spread between Moody's Baa- and Aaa- rated bonds. Stock variance (*SVAR*) is the sum of squared daily returns of the S&P 500 index. We obtain the S&P 500 index return, risk-free rate, dividend and price on the index, bond yields, and stock variance from Professor Goyal's website. We also control for investor sentiment in some of the regressions. We use Baker and Wurgler's (2006) investor sentiment index orthogonalized to macroeconomic variables (*SENT*) and obtain the series from Professor Wurgler's website.

Our sample spans the period from January 1934 to December 2023 (1,080 months), with the exception that the sentiment measure starts from January 1966. Table 1 lists the summary statistics in Panel A and the pairwise correlations in Panel B.

The climate shock measure, *SHK*, has a mean of 0.37 (Fahrenheit degrees) and a median of 0.32, showing that the U.S. temperature has been rising over the 1934-2023 period.[3] The three market crash measures, *D_1y*, *D_2y*, and *D_3y*, have their respective mean of 0.03, 0.07, and 0.09, suggesting that about 3%, 7%, and 9% of months experience a loss in returns of 20%

[3] As a reference, the abnormal temperature provided by NCEI has mean of 0.53, median of 0.50, and standard deviation of 2.12 during 1934-2023.

or more within a one-, two- and three-year horizon, respectively. Notably, the climate shock variable, *SHK*, is positively and significantly correlated with the three market crash measures, with a correlation coefficient equal to 0.05 for *D_1y*, 0.06 for *D_2y*, and 0.03 for *D_3y*, respectively. The positive correlations provide preliminary evidence for the relation between climate shock and market crash, which we analyze in detail below.

3. Empirical method

To examine whether climate shocks predict market crashes, we implement both a linear probability model (LPM) and a probit model. Specifically, in the linear probability model (LPM), we express the probability of a market crash ($P(Crash_t = 1)$) as a liner function of climate shocks ($ClimateShock_t$) and other control variables (x_t). The model is specified as follows:

$$P\left(Crash_{t+j} = 1 | ClimateShock_t, x_t\right) = \alpha + \beta ClimateShock_t + \gamma x_t, \quad (1)$$

where $P(Crash_{t+j}=1)$ is the probability of an equity market crash in period $t+j$, $ClimateShock_t$ represents the climate shock variable at time t, x_t is a vector of control variables at time t, α is the intercept, β and γ are coefficients representing the effect of climate shocks and control variables, respectively.

In the LPM, β represents the change in the probability of a market crash associated with a one-unit change in the climate shock variable. However, since this model is linear, it may produce predicted probabilities that lie outside the [0,1] range, which is a limitation of the LPM.

To circumvent the limitation of LPM, we consider the probit model. In the probit model, the probability of a market crash is modeled as a nonlinear function of climate shocks, using the cumulative distribution function (CDF) of a standard normal distribution. The model is specified as follows:

$$P(Crash_t = 1 | ClimateShock_t, x_t) = \Phi(\alpha + \beta ClimateShock_t + \gamma x_t). \quad (2)$$

Here, $\Phi(\cdot)$ is the CDF of the standard normal distribution, which maps any real-valued input to a value between 0 and 1, the other variables are defined as in the LPM.

In the probit model, the relationship between climate shocks and the probability of a market crash is nonlinear, and the use of the CDF ensures that the predicted probabilities are always within the [0,1] range. The coefficient β in this context affects the argument of the CDF, rather than directly affect the probability. Additionally, the probit model captures potential non-linearities in the relationship between climate shocks and crash probability, offering a more theoretically sound and accurate estimation. To interpret the marginal effect of $ClimateShock_t$ on the crash probability, we calculate the derivative of the CDF with respect to $ClimateShock_t$, which is:

$$Marginal\ Effect = \phi(\alpha + \beta ClimateShock_t + \gamma x_t)\beta, \quad (3)$$

where $\phi(\cdot)$ is the probability density function (PDF) of the standard normal distribution.

4. Results

4.1 Predicting Aggregate Market Crashes

We first examine whether climate shock has power in predicting future aggregate equity market crashes. To do so, we regress the indicators (*D_1y*, *D_2y*, or *D_3y*) for aggregate market crashes within the future one, two, and three years against climate shock (*SHK*) and a set of control variables.

Table 2 reports the results from estimating a linear probability model of the regression. In Columns (1)-(3), the regressions do not include other control variables. The coefficient estimates on *SHK* are all positive. When *D_1y* is the dependent variable, the estimate is 0.004 and statistically significant at the 10% level. When *D_2y* is the dependent variable, the estimate equals 0.008 and is again statistically significant at the 10% level. When *D_3y* is the dependent variable, the estimate equals 0.004 and becomes not statistically significant at the conventional level. Despite the weak statistical significance, these estimates are economically significant. Using the summary statistics in Table 1, a one-standard-deviation increase in *SHK* is associated with an increase in the probability of aggregate equity market crashes in the coming one, two, and three years by 0.81, 1.62, and 0.81 percentage points, respectively. These quantities represent an increase in the aggregate market crash probability by 26.93%, 23.09%, and 8.98% relative to the average crash probability in the coming one-, two-, and three-year horizon, respectively.

In Columns (4)-(6) of Table 2, the regressions include a set of control variables such as dividend yield (*DY*), term spread (*TMS*), default spread (*DEF*), and stock variance (*SVAR*). All the coefficient estimates on *SHK* become statistically insignificant, but they remain economically significant for *D_1y* and *D_2y*. A one-standard-deviation increase in *SHK* is associated with an increase in the aggregate market crash probability by 13.47% and 11.54% in the coming one and two years, respectively. It is worth noting that the coefficient estimates on both *TMS* and *DEF*, *DEF* in particular, are all positive and strongly significant in the three regressions. We suspect that the loss of statistical significance of *SHK* in the regressions is due to that *DEF* sucks up much of the information content of *SHK* for future aggregate market crashes. To verify this conjecture, we run a predictive regression of *SHK* for *DEF* in the coming one, two, and three years. Table 3 reports the predictive regression results, with Columns (1)-(3) and Columns (4)-(6) respectively excluding and including the set of above control variables.

The results in Table 3 lend support to our conjecture. When no control variables are included in the regressions, the estimated coefficients on *SHK* are all positive and statistically significant, respectively at the 1% level for predicting one- and two-year-ahead *DEF* and at the 10% level for three-year-ahead *DEF*. The results largely hold when the regressions include the set of control variables. These estimates suggest that climate shock significantly increases future default spread. As a market crash is often accompanied by and/or preceded by high default spread, the results in Table 2 and Table 3 combined inform one channel via which climate shock predicts future market crash, i.e., by driving up the default spread.

Because the dependent variables are aggregate market crash indicators, which are binary-response variables, we also conduct probit estimations of the predictive regressions. Table 4 reports the estimated marginal effects of the probit regressions. In Columns (1)-(3) whereas *SHK* is the sole predictor, the coefficient estimates are all positive, and the estimate is statistically significant at the 5% level when predicting aggregate market crashes in the coming two years. In Columns (4)-(6) whereas the regressions include control variables, the coefficient estimates remain positive for *D_1y* and *D_2y*, and none of the estimates are statistically significant. Nevertheless, the probit estimation results are quantitatively very similar to the LPM estimation results. Therefore, like the LPM estimates, the Probit estimates are economically significant despite the lack of statistical significance.

It is well documented that extreme climate shock wreak havoc than otherwise. We thus go one further step to investigate the information role of extreme climate shock for future aggregate market crashes. We define two extreme climate shock indicators, one for the left tail and the other for the right tail of the distribution of climate shock. Specifically, *SHK90D* takes a value of one if *SHK* is larger than the 90^{th} percentile cutoff of 3.81, and 0 otherwise; *SHK10D* takes a value of one if *SHK* is smaller than the 10^{th} percentile cutoff of -3.21, and 0 otherwise. We then replace *SHK* with the two extreme shock indicators in the predictive regressions.

Table 5 reports the marginal effect estimates of the Probit regressions that predict the future aggregate market crashes with the two extreme shock indicators. There exists a seemingly asymmetry in the predictive relations between the two extreme climate shocks and subsequent aggregate market crashes. Regardless of inclusion of control variables in the regressions, the estimated marginal effects on *SHK90D* are all positive but not statistically significant across the six columns, and the estimated marginal effects on *SHK10D* are all negative across the six columns and are statistically significant in three out of the six columns. In addition to the opposite signs, the magnitude of the estimated marginal effects on *SHK10D* is uniformly larger than the magnitude of the corresponding marginal effect estimates on *SHK90D*.

Despite the lack of statistical significance for most of the marginal effect estimates, especially those on *SHK90D*, all the estimates are economically significant. Take a look at the estimates in Column (4), whereas control variables are included in predicting the one-year-ahead crash risk. The estimate on *SHK90D* is 0.008, indicating that the hit of an extreme increase in temperature elevates the probability of an aggregate market crash in the coming one year by 0.8 percentage points, which represents an almost 27% jump in the crash probability (relative to the average aggregate market crash probability of 3%). The estimate on *SHK10D* is -0.012, meaning that the incidence of an extreme drop in temperature decreases the probability of an aggregate market crash in the coming one year by 1.2 percentage points, which represents an almost 40% drop in the crash probability (again relative to the average probability of aggregate market crashes of 3%). The estimates in Column (5) imply that a climate shock in the top (bottom) 10 percentile increases (decreases) the probability of aggregate market crash in the subsequent two-year horizon by 20% (25.7%) relative to the average market crash probability. The estimates in Column (6) suggest that a climate shock in the top (bottom) 10 percentile raises (reduces) the probability of aggregate market crash in the coming three-year horizon by 8% (11%). The corresponding economic significance with the marginal effect estimates in Columns (1)-(3) has even greater magnitude.

The opposite signs on the estimates of *SHK90D* and *SHK10D* deserve a further discussion. The positive estimates on *SHK90D* imply that extreme rises in temperature tend to increase the chance of an aggregate market crash in the coming few years. The negative estimates on *SHK10D* suggest the opposite – extreme drops in temperature reduce the probability of an aggregate market crash in the coming few years. Extreme increases (decreases) in temperature, i.e., at least 3.81 degrees higher (3.21 degrees lower) than the normal temperature in our case, usually point to abnormally hot (cold) weather. Therefore, one way to rationalize the opposite predictive relations between aggregate market crashes and the bifurcating temperature shocks is that abnormally hot and cold weather affect human psychology and behavior differently. In an abnormally hot weather, investors can become (over)optimistic/confident and trade, purchase in particular, stocks aggressively [e.g., Hirschleifer and Shumway, 2003]. This drives up current stock prices, leading to overpricing of assets and thus aggregate market crashes in the future. To the contrary, when weather is abnormally cold, investors can become moody and (over-)pessimistic and trade less and/or sell more intensively [e.g., Saunders, 1993; Kamstra, Kramer, and Levi, 2003; deHaan, Madsen, and Piotroski, 2017]. As a result, current stock prices are depressed in abnormally cold weather and, in turn, the likelihood of aggregate market crashes in the future declines.

4.2 Predicting Industry Market Crashes

In the above subsection we look at the predictive relation between climate shock and market crashes at the aggregate level. In this subsection we assess the predictive relation at the disaggregate level. For this purpose, we zero in on market crashes at the industry level. We use the Fama-French 10 industry returns, and we follow the construction of the aggregate market crash indicators to define three market crash indicators for each industry.

Table 6 reports the results of estimating the panel probit model for industry market crashes in the coming one-, two-, and three-year horizons. We include in all regressions industry-fixed effects to control for time-invariant industry characteristics. The fixed effects also allow us to control for substantial across-industry variations in the regressions. In Columns (1)-(3), climate shock is the sole crash predictor. The three coefficient estimates on *SHK* are all positive, respectively equal to 0.052, 0.049, and 0.048 for the industry market crashes in the one-, two, and three-year horizons. Moreover, the three estimates on *SHK* are all statistically significant at the 1% level. In Columns (4)-(6), the regressions also include the four control variables: *DY, TMS*, *DEF* and *SVAR*. The three estimates on *SHK* remain positive and statistically significant at the 1% level. The results show that climate shock increases industry market crashes in the upcoming few years.

For better interpretation of the results, we present the marginal effect estimates of the panel probit model in Table 7. Consistent with the parameter estimates, all the estimated marginal effects are positive and strongly significant at the 1% level, regardless of controlling for other predictors in the regressions. Without control variables, the estimated marginal effects are 0.006, 0.009, and 0.011 for the industry market crashes in the coming one-, two-, and three-year horizons, respectively. After including the control variables, the estimated marginal effects are 0.004, 0.005, and 0.006 for the industry market crashes in the coming one-, two-, and three-year horizons, respectively. These estimates are economically significant. Using the latter set of estimates, we infer that a one-standard-deviation increase in *SHK* raises the probability of an industry market crash in the next one, two, and three years by 0.81, 1.01, and 1.21 percentage points, respectively. Relative to the average industry market crash probabilities of 9.87%, 16.2%, and 21.5% in the one-, two-, and three-year horizon, these figures translate into increases in the probability of an industry market crash in the corresponding horizons by 8.19%, 6.23%, and 5.51%, respectively. We obtain larger values in the economic significance with the former set of marginal effect estimates.

It is worth noting that the marginal effect estimates are considerably larger for industry market crashes as reported in Table 7 than the marginal effect estimates for aggregate market crashes as reported in Table 4. This result makes sense because the aggregate market is well diversified and exhibits smaller swings, hence experiences less crashes, than industries do. In other words, climate shock has much larger effects on market crashes at the industry level.

We proceed to assess whether the two tails of the climate shock predict industry market crashes in a symmetrical way. We replace *SHK* with the two indicators for the left and right tails, *SHK10D* and *SHK90D*, in the predictive models and conduct Probit estimations. Table 8 reports the marginal effect estimates.

There exists a seemingly asymmetry in the roles of the left and right tails of climate shock in predicting the industry market crashes in the coming one-, two-, and three-year horizon. Across the six columns of this table, the estimated coefficients on *SHK90D* are all positive and statistically significant at the 10% or stronger level, and the estimated coefficients on *SHK10D* are all negative and statistically significant at the 1% level. The results show that extreme rises in temperature significantly increase the probability of industry market crashes in the subsequent few years, and the extreme decreases in temperature significantly reduce the industry crash risk in the following few years.

The marginal effect estimates are economically significant. Use the estimates in Columns (4)-(6) as illustration. Relative to the "normal" level of temperature shock, i.e., ranging from the 10^{th} percentile to the 90^{th} percentile of the shock distribution, a climate shock in the top 10^{th} percentile will raise the probability of industry market crashes in the coming one-, two-, and three-year horizon by 2.3, 3.3, and 3.0 percentage points, respectively. These figures represent a respective 23.30%, 20.37%, and 13.64% jump in the crash probabilities (relative to the average industry market crash probabilities) in the three horizons. Similarly, relative to the "normal" level of temperature shock, a climate shock in the bottom 10^{th} percentile will reduce the probability of industry market crashes in the coming one-, two-, and three-year horizon by 3.1, 3.4, and 4.3 percentage points, respectively. Relative to the average crash probabilities, these figures represent a respective 31.41%, 20.99%, and 19.55% decline in the probability of an industry market crash in the three horizons.

When combining the results in Tables 5 and 7, we infer that the asymmetric effects of the climate shock in the left and right tails on future market crash risk are stronger at the industry level than at the aggregate level. This is again consistent with the fact that the aggregate market is well diversified and tends to crash less than industries.

4. Conclusions

In this paper, we assess whether climate change, proxied by temperature shock, predicts financial market crashes in the coming one-, two-, and three-year horizon. Using data over the 1934-2023 period, we find that climate change is positively associated with aggregate market crashes within the subsequent three years. The estimates, albeit somewhat weak in statistical significance, are of considerable economic significance. Using the estimates obtained with the climate shock as the sole predictor, we infer that a one-standard-deviation increase in the shock heightens the aggregate market crash probability by about 26.9%, 23.1%, and 9.0% (relative to the average crash probability) in the one-, two-, and three-year horizon, respectively. Based on the estimates obtained after controlling for usual equity premium predictors in the regressions, a one-standard-deviation increase in the shock elevates the probability of an aggregate market crash within the coming one- and two-year horizon by about 13.5% and 11.5%, respectively.

There exits seemingly asymmetry for the shock in the left and right tails to predict aggregate market crashes. A climate shock in the top 10 percentile increases the market crash probability by about 27%, 20%, and 8% in the subsequent one-, two, and three-year horizon, respectively. In contrast, a climate shock in the bottom 10 percentile significantly decreases the market crash probability by about 40%, 26%, and 11% in the coming one-, two, and three-year horizon, respectively. This asymmetry reveals that abnormally hot weather and abnormally cold weather affect the aggregate equity market in qualitatively opposite ways.

The predictive relation between climate shock and market crash risk as well as the asymmetry pertaining to climate shock in the left tail versus climate shock in the right tail extend to the industry level. Notably, the results are more pronounced at the industry level than at the aggregate level, reflecting that the aggregate market is well diversified and tends to experience less crashes than industries.

Our results have implications for the development of investment strategy, insurance strategy, and risk management. Our results also shed a light on including climate shock as an early warning indicator for future financial crises. Additionally, our analysis informs the policy response to challenges posed by climate change, global warming in particular.

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Table 1

Descriptive statistics and correlations

Summary statistics in panel A are reported for climate shock (shk), one-year ahead, two-year ahead , and three-year ahead log S&P index excess returns (r_1y, r_2y, and r_3y), one-year ahead, two-year ahead , and three-year ahead market crash (D_1y, D_2y, and D_3y), term spread (tms), default spread (def), stock variance (svar), and sentiment (SENT). The crash indicator is regressed on climate shock (shk), which is the difference between the current temperature and the mean temperature of the previous 40 years. Panel B reports pairwise correlations. The sample period spans from 1934:01–2023:12.

Panel A: Descriptive Statistics

	n	mean	sd	median	min	max	skew	kurtosis
shk	1080	0.37	2.02	0.32	-7.54	8.10	-0.05	1.14
r_1y	1069	0.04	0.17	0.05	-0.75	0.56	-0.66	1.11
r_2y	1057	0.04	0.12	0.04	-0.35	0.37	-0.40	0.35
r_3y	1045	0.03	0.09	0.04	-0.22	0.22	-0.34	-0.27
D_1y	1068	0.03	0.18	0.00	0.00	1.00	5.16	24.65
D_2y	1056	0.07	0.25	0.00	0.00	1.00	3.42	9.72
D_3y	1044	0.09	0.29	0.00	0.00	1.00	2.78	5.74
DY	1080	0.29	0.21	0.20	0.06	1.68	1.72	3.84
tms	1080	1.69	1.29	1.71	-3.65	4.55	-0.22	0.24
def	1080	1.04	0.51	0.88	0.32	3.38	1.52	2.41
svar	1080	0.23	0.46	0.12	0.01	7.32	9.68	126.61
SENT	684	0.00	1.00	0.00	-2.49	3.21	0.16	0.86

Panel B: Correlations

	shk	r_1y	r_2y	r_3y	D_1y	D_2y	D_3y	DY	tms	def	svar
r_1y	0.03										
r_2y	0.06	0.69									
r_3y	0.02	0.52	0.79								
D_1y	0.05	-0.21	-0.19	-0.20							
D_2y	0.06	-0.16	-0.26	-0.27	0.70						
D_3y	0.03	-0.04	-0.15	-0.23	0.59	0.85					
DY	-0.06	0.08	0.10	0.11	0.07	0.08	0.08				
tms	0.05	0.16	0.20	0.25	0.12	0.16	0.22	-0.06			
def	0.10	0.08	0.04	-0.04	0.25	0.36	0.44	0.14	0.29		
svar	0.06	-0.02	0.01	-0.05	0.11	0.13	0.12	-0.01	0.12	0.35	
SENT	0.07	-0.09	0.00	0.14	0.12	0.16	0.21	-0.17	-0.04	-0.03	0.01

Table 2

Climate Shock Predicts Increased Stock Market Crash

This table reports estimates from the linear probability model (LPM) regression for market crash in the subsequent one, two, and three years. The dependent variable (D_1y, D_2y, or D_3y) is the crash indicator, which takes a value of 1 if there is a future equity crash—defined as a monthly drop of −20% or more—in the next K years (K = 1, 2, and 3), and 0 otherwise. The crash indicator is regressed on climate shock (shk), which is the difference between the current temperature and the mean temperature of the previous 40 years. The regression also considers several subsets of control variables known to predict the equity premium, including dividend yield (DY), term spread (tms), default spread (def), and stock variance (svar). Standard errors, shown in brackets, are computed using White's (1980) robust standard errors. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from January 1934 to December 2023.

	Dependent variable					
	D_1y	D_2y	D_3y	D_1y	D_2y	D_3y
	(1)	(2)	(3)	(4)	(5)	(6)
shk	0.004*	0.008*	0.004	0.002	0.004	-0.002
	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.004)
DY				4.164	4.374	4.752
				(2.831)	(3.322)	(3.499)
tms				0.778***	1.143***	2.366***
				(0.273)	(0.393)	(0.530)
def				7.727***	16.580***	23.485***
				(1.639)	(2.252)	(2.518)
svar				1.004	0.038	-2.014
				(1.834)	(2.025)	(2.104)
Constant	0.032***	0.065***	0.092***	-0.075***	-0.138***	-0.200***
	(0.005)	(0.008)	(0.009)	(-0.016)	(-0.020)	(-0.023)
Observations	1,068	1,056	1,044	1,068	1,056	1,044
Adjusted R2	0.002	0.003	-0.0002	0.065	0.132	0.199
F-Statistic	2.686	4.231**	0.829	15.877***	33.182***	52.733***

Table 3
Climate shock predicts default spreads

This table reports estimates from the regression for default spreads in the subsequent one, two, and three years (def_1y, def_2y, or def_3y) on climate shock (shk), which is the difference between the current temperature and the mean temperature of the previous 40 years. The regression also considers several subsets of control variables known to predict the equity premium, including dividend yield (DY), term spread (tms), default spread (def), and stock variance (svar). Standard errors, shown in brackets, are computed using robust standard errors (White, 1980). $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from January 1934 to December 2023.

	def_1y	def_2y	def_3y	def_1y	def_2y	def_3y
	(1)	(2)	(3)	(4)	(5)	(6)
shk	0.002***	0.002**	0.001*	0.002**	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
DY				3.797***	2.654***	1.863**
				(0.885)	(0.843)	(0.807)
tms				0.752***	0.243	0.069
				(0.154)	(0.151)	(0.138)
svar				3.811***	2.911***	2.431***
				(1.167)	(0.988)	(0.837)
Constant	0.122***	0.121***	0.121***	0.090***	0.103***	0.109***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Nobs	1,069	1,057	1,045	1,069	1,057	1,045
Adj R2	0.005	0.004	0.003	0.157	0.086	0.06
F Stat	6.581**	5.591**	3.632*	50.597***	25.805***	17.645***

Table 4

Climate Shock Predicts Increased Stock Market Crash: Marginal Effect

This table reports estimates from the probit model regression for market crash in the subsequent one, two, and three years. All reported estimates are marginal effects. The dependent variable (D_1y, D_2y, or D_3y) is the crash indicator, which takes a value of 1 if there is a future equity crash—defined as a monthly drop of −20% or more—in the next K years (K = 1, 2, and 3), and 0 otherwise. The crash indicator is regressed on climate shock (shk), which is the difference between the current temperature and the mean temperature of the previous 40 years. The regression also considers several subsets of control variables known to predict the equity premium, including dividend yield (DY), term spread (tms), default spread (def), and stock variance (svar). Robust standard errors are in brackets. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from January 1934 to December 2023.

	Dependent variable					
	D_1y	D_2y	D_3y	D_1y	D_2y	D_3y
	(1)	(2)	(3)	(4)	(5)	(6)
shk	0.004	0.008^{**}	0.004	0.002	0.003	-0.001
	(0.003)	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)
DY				1.962	2.311	2.770
				(1.246)	(2.117)	(2.395)
tms				0.783^{***}	1.302^{***}	2.331^{***}
				(0.220)	(0.297)	(0.389)
def				3.108^{***}	7.918^{***}	11.040^{***}
				(0.713)	(1.173)	(1.380)
svar				-0.122	-1.124	-2.830^{*}
				(0.604)	(1.165)	(1.541)
Observations	1080	1080	1080	1080	1080	1080

Table 5
Climate Shock Predicts Increased Stock Market Crash: Asymmetric Marginal Effect

This table reports estimates from the probit model regression for market crash in the subsequent one, two, and three years. All reported estimates are marginal effects. The dependent variable (D_1y, D_2y, or D_3y) is the crash indicator, which takes a value of 1 if there is a future equity crash—defined as a monthly drop of −20% or more—in the next K years (K = 1, 2, and 3), and 0 otherwise. The crash indicator is regressed on two climate shock dummies, shk90D takes a value of if shk is above 90th percentile, and 0 otherwise, shk10D takes a value of 1 if shk is below 10th percentile, and 0 otherwise. The regression also considers several subsets of control variables known to predict the equity premium, including dividend yield (DY), term spread (tms), default spread (def), and stock variance (svar). Robust standard errors are in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from January 1934 to December 2023.

	Dependent variable					
	D_1y	D_2y	D_3y	D_1y	D_2y	D_3y
	(1)	(2)	(3)	(4)	(5)	(6)
shk90D	0.021	0.035	0.033	0.008	0.014	0.007
	(0.021)	(0.030)	(0.034)	(0.013)	(0.020)	(0.020)
shk10D	-0.026**	-0.042**	-0.039	-0.012*	-0.018	-0.010
	(0.012)	(0.019)	(0.025)	(0.007)	(0.014)	(0.016)
dp				1.857	2.166	2.775
				(1.214)	(2.092)	(2.379)
tms				0.741***	1.247***	2.308***
				(0.210)	(0.292)	(0.388)
def				3.081***	7.929***	10.943***
				(0.727)	(1.176)	(1.374)
svar				-0.16	-1.18	-2.868*
				(-0.601)	(-1.158)	(-1.541)
Observations	1080	1080	1080	1080	1080	1080

Table 6

Climate Shock Predicts Increased Industry Stock Crash: Probit Model

This table reports estimates from the panel probit regression for industry equity crash in the subsequent one, two, and three years. The 10 industry portfolios defined in Fama and French (1997) and assign the industry loadings to individual companies by matching on SIC codes. The dependent variable (D_1y, D_2y, or D_3y) is the crash indicator, which takes a value of 1 if there is a future industry equity crash—defined as a monthly drop of -20% or more—in the next K years (K = 1, 2, and 3), and 0 otherwise. The crash indicator is regressed on climate shock (shk), which is the difference between the current temperature and the mean temperature of the previous 40 years. The regression also considers several subsets of control variables known to predict the equity premium, including dividend yield (DY), term spread (tms), default spread (def), and stock variance (svar). Standard errors, shown in brackets, are computed using White's (1980) robust standard errors. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from January 1934 to December 2023.

	Dependent variable					
	D_1y	D_2y	D_3y	D_1y	D_2y	D_3y
	(1)	(2)	(3)	(4)	(5)	(6)
shk	0.052***	0.049***	0.048***	0.037***	0.030***	0.027***
	(0.010)	(0.008)	(0.007)	(0.010)	(0.008)	(0.008)
DY				-57.093***	-89.091***	-101.994***
				(11.166)	(9.704)	(9.031)
tms				-5.771***	-9.392***	-6.168***
				(1.613)	(1.372)	(1.272)
def				64.197***	77.949***	87.795***
				(3.805)	(3.404)	(3.291)
svar				13.278***	5.800	-2.185
				(3.246)	(3.212)	(3.321)
Log Likelihood	-2466.45	-3700.48	-4469.18	-2279.01	-3380.34	-4028.76
Industry effect	Y	Y	Y	Y	Y	Y
Nobs	10681	10562	10442	10681	10562	10442

Table 7

Climate Shock Predicts Increased Industry Stock Crash: Probit Model Marginal Effect

This table reports estimates from the panel probit model regression for industry equity crash in the subsequent one, two, and three years. All reported estimates are marginal effects. The 10 industry portfolios defined in Fama and French (1997) and assign the industry loadings to individual companies by matching on SIC codes. The dependent variable (D_1y, D_2y, or D_3y) is the industry equity crash indicator, which takes a value of 1 if there is a future industry equity crash—defined as a monthly drop of -20% or more—in the next K years (K = 1, 2, and 3), and 0 otherwise. The crash indicator is regressed on climate shock (shk), which is the difference between the current temperature and the mean temperature of the previous 40 years. The regression also considers several subsets of control variables known to predict the equity premium, including dividend yield (DY), term spread (tms), default spread (def), and stock variance (svar). Standard errors are in brackets. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from January 1934 to December 2023.

	Dependent variable					
	D_1y	D_2y	D_3y	D_1y	D_2y	D_3y
	(1)	(2)	(3)	(4)	(5)	(6)
shk	0.006***	0.009***	0.011***	0.004***	0.005***	0.006***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
DY				-6.400***	-15.362***	-21.515***
				(1.317)	(1.719)	(1.887)
tms				-0.647***	-1.620***	-1.301***
				(0.161)	(0.215)	(0.254)
def				7.197***	13.441***	18.52***
				(0.404)	(0.575)	(0.680)
svar				1.488***	1.000	-0.461
				(0.344)	(0.516)	(-0.692)
Industry Eff.	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-2466.448	-3700.482	-4469.183	-2279.005	-3380.344	-4028.76
Nobs	10681	10562	10442	10681	10562	10442

Table 8

Climate Shock Predicts Increased Industry Stock Crash: Asymmetric Marginal Effect

This table reports estimates from the panel probit model regression for industry equity crash in the subsequent one, two, and three years. All reported estimates are marginal effects. The 10 industry portfolios defined in Fama and French (1997) and assign the industry loadings to individual companies by matching on SIC codes. The dependent variable (D_1y, D_2y, or D_3y) is the industry equity crash indicator, which takes a value of 1 if there is a future industry equity crash—defined as a monthly drop of -20% or more—in the next K years (K = 1, 2, and 3), and 0 otherwise. The crash indicator is regressed on two climate shock dummies, shk_90D takes a value of 1 if shk is above the 90th percentile, and 0 otherwise, shk_10D takes a value of 1 if shk is below the 10th percentile, and 0 otherwise. The regression also considers several subsets of control variables known to predict the equity premium, including dividend yield (DY), term spread (tms), default spread (def), and stock variance (svar). Standard errors are in brackets. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from January 1934 to December 2023.

	Dependent variable					
	D_1y	D_2y	D_3y	D_1y	D_2y	D_3y
	(1)	(2)	(3)	(4)	(5)	(6)
shk_90D	0.032***	0.049***	0.056***	0.023**	0.033**	0.030*
	(0.009)	(0.012)	(0.013)	(0.008)	(0.011)	(0.012)
shk_10D	-0.038***	-0.047***	-0.06***	-0.031***	-0.034***	-0.043***
	(-0.006)	(-0.009)	(-0.010)	(-0.006)	(-0.009)	(-0.010)
DY				-6.499***	-15.494***	-21.699***
				(-1.317)	(-1.720)	(-1.891)
tms				-0.714***	-1.701***	-1.386***
				(-0.160)	(-0.214)	(-0.254)
def				7.223***	13.469***	18.558***
				(0.404)	(0.574)	(0.679)
svar				1.435***	0.949	-0.546
				(0.337)	(0.508)	(0.695)
Industry Eff.	Yes	Yes	Yes	Yes	Yes	Yes
Log like	-2457.527	-3695.358	-4463.76	-2270.858	-3373.921	-4022.575
Nobs	10681	10562	10442	10681	10562	10442