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Physical Climate Change Risks and the Sovereign Creditworthiness of Emerging Economies*

Abstract

I show that rising temperatures can detrimentally affect the sovereign creditworthiness of emerging economies. To this end, I collect long-term monthly temperature data of 54 emerging countries. I calculate a country's temperature deviation from its historical average, which approximates present day climate change trends. Running regressions from 1994m1-2018m12, I find that higher temperature anomalies lower sovereign bond performances (i.e. increase sovereign risk) significantly for countries that are warmer on average and have lower seasonality. The estimated magnitudes suggest that affected countries likely face significant increases in their sovereign borrowing costs if temperatures continue to rise due to climate change. However, results indicate that stronger institutions can make a country more resilient towards temperature shocks, which holds independent of a country's climate.

Keywords: climate risks, sovereign creditworthiness, international finance, emerging market economies, institutions

JEL classification: G15, H63, O13, Q54, Q56

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1 Introduction

As of 2020, human activities are estimated to have caused approximately 1.0°C of global warming compared to pre-industrial levels (IPCC 2018). Climate-related natural disasters, infectious diseases, species extinction and threats to economic prosperity as well as food, health and water supply are projected to increase dramatically with further warming. However, the IPCC (2018) also emphasizes that the 1.0°C increase witnessed so far has already led to more extreme weather events, changing natural systems and economic damages. Furthermore, the report states that the burden of climate change will be particularly heavy for developing countries in the global South.

In this paper, I exploit temperature fluctuations of past years which represent physical climate change risks in line with the 1.0°C warming witnessed so far. I contribute to the literature by linking these movements in temperature to the sovereign creditworthiness of, potentially climate-vulnerable, emerging market economies. Though the literature on the economic effects of temperature fluctuations is rich, the link to sovereign bond performances or sovereign risk has so far been missing.

Despite this gap in the literature, climate change can pose a significant threat for the creditworthiness of sovereigns according to several regulatory bodies. For instance, a report on the financial risks from climate change by the Bank of England (2018) states:

> *"The increasing frequency of severe weather events could also impact macroeconomic conditions through sustained damage to national infrastructure and weaken fundamental factors such as economic growth, employment, and inflation. This could have implications for the market price of sovereign debt for those countries most susceptible to the physical impacts of climate change."*[1]

Furthermore, rating agencies such as Moody's (2016) have started incorporating the credit implications of climate change for sovereign issuers. These developments matter, as sovereign creditworthiness and associated bond costs are crucial for all governments. Rising borrowing costs compensate bondholders for higher risks, but can also push countries into crisis and default. Even in the absence of debt crises, any unit of currency that is spent on borrowing costs can no longer be used for other expenditures such as adaptions to climate change.

[1]Similar remarks can be found by the ECB (2019), stating: *"sovereign risks could increase for countries with carbon-intensive industries."*

Therefore, I extend the literature on climate risks, in the form of temperature fluctuations, in connection with financial markets, in the form of sovereign bond returns. Figure 1 illustrates the main idea of my empirical approach. It depicts the mean annual temperature of the 54 countries in my panel from 1901 to 2018, showing an upward trend since the second half of the 20th century. The red line shows the constant temperature average from 1901 to 1950. From 1994 onward, which is the start of my estimation period and the shaded area in the graph, I calculate a country's temperature deviation from its 1901-1950 average. This temperature anomaly variable has a mean of 0.84°C which is close to the global warming trend of 1°C estimated by the IPCC (2018).

- Figure 1 around here -

In my estimation, I follow the "new approach" outlined by Dell et al. (2014). Using monthly data for 54 emerging economies from 1994 to 2018, I regress market returns of the Emerging Market Bond Index (EMBI), a common measure for sovereign debt performance, on the described temperature anomaly fluctuations. I control for precipitation and include country and region-time fixed effects on the month-year level. The captured temperature shocks are thus idiosyncratic and account for weather trends common to each region. Building on a rich literature that links temperature increases to lower GDP growth in poorer and warmer countries (Burke et al. 2015, Dell et al. 2012), reduced firm productivity and output (Zhang et al. 2018, Adhvaryuy et al. 2019), decreasing labor supply (Graff Zivin & Neidell 2014) and more interpersonal and civil conflict (Hsiang et al. 2013), I expect rising temperatures compared to a country's historical temperature average to lead to lower sovereign debt performance (i.e. increasing sovereign risk).

My results indicate that the effect of rising temperature anomalies on sovereign creditworthiness critically hinges on a country's economic and climatic profile: Warm countries are significantly more susceptible to temperature shocks than cold or mild-tempered countries, which echoes the results of Burke et al. (2015). For countries with very high average annual temperatures (> 25°C), a 1°C increase in monthly temperature compared to a country's historical average lowers EMBI returns by 0.464 percentage points on average. This effect corresponds to 11.9% of the EMBI returns' overall standard deviation. Thus, in a 2°C global warming scenario, EMBI returns (in percentage points) could be lowered for affected countries by roughly a quarter of their overall standard deviation. This magnitude is non-negligible and could lead to rising sovereign borrowing costs or even defaults for warmer countries in the next decades. Such future projections must of course be treated carefully, as they abstain from countries' adaption strategies towards climate change but also from potentially non-linearly aggravating weather effects that are entailed by continuously rising temperatures (see Bolton et al. (2020)). However, if the past temperature anomaly shocks captured in this paper are any guidance, warm countries could bear a major burden from future temperature increases in the form of lower sovereign creditworthiness.

Related to the warmness of a country, I find that countries with lower temperature-seasonality suffer statistically and economically significantly more from temperature increases with respect to their sovereign risk level than countries with more volatile seasons. This result holds either for grouping countries into different bins of seasonality or for dividing the temperature anomaly measure by a country's standard deviation of monthly temperature.

Next, I exploit the monthly frequency of my data. I test if temperature shock effects differ in warmer compared to colder months or in summer compared to winter. However, after adjusting the months in southern hemisphere countries to the northern hemisphere scale, I find no statistical evidence that a temperature shock in warmer months has significantly different implications for sovereign creditworthiness than shocks in colder months, or differs in summer compared to winter. Put together with the previous evidence, this result suggests that the overall warm- or coldness of a country is what matters for temperature-induced sovereign risk, not the within-year seasonality of the weather.

Following the analysis of a country's climatic profile, I test if different economic sector specializations could be related to the strength of historical temperature shocks on sovereign debt performance. To this end, I interact the temperature anomaly measure with the specialization of a country in terms of agriculture, manufacturing, services or natural resources. However, these specifications do not yield any statistical patterns indicating that countries with higher agricultural shares on GDP, more service sector employees or larger rents from natural resources such as oil are more (or less) susceptible to temperature shocks with respect to their sovereign risk. My results do not rule out that potentially stranded industries, such as fossil fuels, may affect sovereign debt prices in the future, once their business models have become under stronger pressure. Still, the effect seems to be weak during my estimation period or not connected to temperature shocks.

What instead holds remarkably well throughout the analysis is the conditioning impact of institutional quality on temperature-induced sovereign risk. Countries with weaker rule of law, control of corruption, civil rights, democratic governments or less progressive tax systems face a statistically significantly stronger marginal effect of temperature increases that is detrimental to their sovereign creditworthiness. Next to these more traditional institutional variables, climate-related metrics yield a similar conclusion: Countries with lower values in the ND-Gain index, which measures both the adaptiveness and vulnerability of a country towards climate change, face significantly higher temperature shock effects on their sovereign risk level. Disentangling the ND-Gain index reveals that this effect is driven more by the adaptive readiness than the vulnerability part of the index. These results suggest that higher overall institutional quality, both traditional and climate-related, could improve the resilience and adaptiveness of emerging economies towards climate change.

I conduct encompassing robustness tests to demonstrate the stability of my results. These procedures include changing the fixed effects specification, dependent variable, historical average period and lag structure of temperature shocks. I also drop certain countries from the analysis, firstly if they have few EMBI data points, secondly if their landmass is among the ten largest countries. In addition, I test if more volatile weather periods can also impair sovereign bond performance, for which I find confirmation. Lastly, I analyze if the temperature effects changed after the Paris Agreement in December 2015, which does not seem to be the case.

In sum, my evidence suggests that historical temperature deviations, approximating physical climate change, lower sovereign bond performances (i.e. increase sovereign risk) significantly for countries that are: (i) warmer, (ii) have lower seasonality, (iii) and have lower institutional quality, both for traditional and climate-related metrics. I also find evidence that poorer countries suffer more from temperature shocks. However, these factors are correlated as poorer countries tend to have worse institutions. In addition, it is difficult to disentangle the long-run effects of climate zones on the creation of institutions or the wealth of nations (see Acemoglu et al. (2002) for a discussion).

I shed some light on these interrelations by combining all relevant channels, i.e. warmness, poverty and institutional quality, in one regression. My evidence suggests that the effect of poorer countries suffering stronger from temperature shocks is indeed driven by these countries' tendencies to have worse institutions. However, both the institutional and the warmness channel remain statistically significant in the same specification, suggesting that stronger institutions can provide resilience towards temperature shocks, independent of the warmness of a country.

Though any further disentanglement of these channels is beyond the scope of this paper, what matters for the policy implications is the finding that countries with warmer weather and lower institutional quality have so far been hit significantly harder by temperature anomaly shocks with respect to their sovereign creditworthiness. This result is an important extension to the still young literature on climate risks and financial markets. If past trends are any guidance, affected countries could face meaningful increases in their sovereign debt costs or even debt crises as climate change intensifies.

The rest of the paper is structured as follows. Section 2 provides a framework on how to think about physical climate change risk and its relationship to sovereign risk. Section 3 introduces the data and provides summary statistics. In the following, Section 4 describes the empirical framework and main regression results. Section 5 investigates the climatic and economic profiles of countries and their relationship to temperature-induced sovereign risk. The subsequent Section 6 provides encompassing robustness checks. Section 7 concludes.

2 Physical Climate Change Risk

2.1 Physical Climate Change Risk in Contrast to Transition Risk

The following section provides a framework on how to think about climate change risks in a sovereign bond context. Table 1 by the Bank of England (2018) depicts the distinction between *physical* and *transition* risks as the two main channels of how climate change can lead to economic impairments.

- Table 1 around here -

Physical risks describe the materializing damages from climate change. They can arise from extreme weather events or natural disasters such as droughts, wildfires, sea level rises or floods. Regions hit by such disasters can face losses in terms of human lives, critical infrastructure, food supply, firm assets or their capital stock (see also Bolton et al. (2020)). As further global warming likely entails irreversible tipping points, these damages could lead to non-transitory, lasting disruptions (Ripple et al. 2019). According to the insurance data used by NGO Germanwatch (2019), the damages from extreme weather events worldwide between 1999 and 2018 amounted to $3.54 trillion (in purchasing power parities). Physical climate risks can materialize as a mortgage risk for homeowners that lose their property, a credit risk for banks that lend to e.g. flood-impaired firms (Koetter et al. (2019)), an underwriting risk for insurance companies (Financial Stability Institute 2019) and, as demonstrated in this paper, a market risk for sovereigns bonds of countries most susceptible to the physical impacts of climate change.

In contrast, transition risks describe the adjustment towards a low-carbon economy and the expected damages and costs associated therewith. Therefore, these risks are more forward-looking as (expected) changes in environmental policies or sentiments could threaten, for instance, the business model of certain firms. Should investors reassess the viability of e.g. a fossil-energy-intensive industry as tougher climate laws are implemented, the stock price of affected firms might fall. Such a shock would likely spill-over to banks, pension funds and other investors with exposures towards stranded industries, which is referred to as a "carbon bubble" (see ESRB (2016) for an associated systemic risk analysis and Delis et al. (2018) for how banks price carbon bubble risks).

An example of transition risks in a government bond context that contrasts the physical risks in this paper is by Painter (2020). He shows that US municipalities that face stronger sea level increases in the future have higher issuance costs for their municipality bonds today. Because of its forward-looking nature, this effect demonstrates a transition risk. As projected climate damages from sea level increases rise over time, the results are driven by long-term bonds. In addition, the pricing effect increased around the release of the Stern report on climate change in 2006. Though not shown by Painter (2020), it could likely be the case that such re-pricing of climate-sensitive assets was even more pronounced in recent years as global warming became a major concern for the financial industry (see Boston Common Asset Management (2018) for a survey of global banks and Bolton & Kacperczyk (2020) for asset pricing effects of firms' CO2 emissions).

In contrast to forward-looking transition risks, this paper, and the literature on temperature effects in general, analyze already materialized impacts of past temperature fluctuations.

Temperature increases are associated with extreme weather events or hotter years and influence economic activities along several dimensions, as the next section demonstrates. Of course, both risk channels cannot be isolated completely from another: A wildfire might entail vast economic damages (physical risk), but also change perceptions of investors regarding the susceptibility of the affected region towards more wildfires in the future (transition risk). It is beyond the scope of this paper to disentangle these risk effects. Nevertheless, I will label temperature fluctuations as a form of physical risk in the following due to their primary impact on current economic activities.

2.2 Physical Climate Change and Sovereign Creditworthiness

Temperature fluctuations have economic effects that can likely spill-over to sovereign risk. Dell et al. (2012) show that higher temperatures reduce the GDP growth rate of poorer countries. This effect is driven by lower agricultural and industrial value-added and increasing political instability during warmer years. Related, Burke et al. (2015) show that temperature has a non-linear effect on GDP growth, with warmer countries' economies being hit significantly more negative by higher temperatures than colder or milder-tempered countries for which temperature increases are negligible or even beneficial. Heal & Park (2014) and Deryugina & Hsiang (2014) obtain similar results. Regarding the research agenda of this paper, it is likely that macroeconomic fundamentals like GDP growth or related fiscal conditions impact sovereign bond pricing (see Hilscher & Nosbusch (2010) or Gupta et al. (2008)).

With respect to the microeconomic channels behind the temperature-GDP relationship, Zhang et al. (2018) find that more hot days per year in a Chinese region significantly reduce output and productivity of local firms. Using climate prediction models, the authors derive that these effects could lower Chinese manufacturing output by 12% annually by 2050. Adhvaryuy et al. (2019), Cachon et al. (2012) and Somanathan et al. (2018) obtain similar evidence, confirming that labor becomes less productive with hotter days. In addition, Graff Zivin & Neidell (2014) demonstrate that individual labor supply decreases with more warm days in a year. One notable exception to this micro evidence is by Addoum et al. (2020) who find weak effects of temperature shocks on US firm sales.

Climate and weather patterns also influence conflict and political stability. Hsiang et al. (2013) summarize in a meta study several contributions that link increasing temperatures to more interpersonal conflict and crime, but also riots, civil conflict or ultimately civil war (see also Burke et al. (2009)). Sovereign bond yields are known to respond to political conditions (Eichler 2014) and it is highly plausible for temperature-induced political instability to increase sovereign risk.

Though not every natural disaster can be directly linked to climate change, the IPCC (2018) projects climate-related disasters to increase with further global warming. Figure 2 depicts the total number of climate-related natural disasters such as floods, droughts and wildfires of the countries in my panel next to the average sample temperature from 1901 to 2018. There is a positive correlation between the rising occurrence of natural disasters and increasing temperature, however, this relationship is at least partially driven by better detection and recording of disasters. Nevertheless, the temperature anomaly measure in this paper picks up natural disasters to some extend, as shown in the next section, and it is intuitive to assume that severe disasters are detrimental to the economy and sovereign creditworthiness of a country (Felbermayr & Gröschl 2014).

- Figure 2 around here -

As I use the market return of a financial asset as my dependent variable, it is worth noting that Bansal et al. (2016) demonstrate that most US equities have a negative exposure coefficient towards long-run temperature fluctuations. Temperature patterns and other climate-related measures are thus priced in financial assets (Bolton & Kacperczyk 2020).

The literature on the effects of temperature anomalies on sovereign creditworthiness is so far scarce, which is why this paper adds significant value to this debate. Next to cited work by Painter (2020), another paper that looks at the relationship between sovereign borrowing costs and climate change more general is by Kling et al. (2018). The authors regress bond costs on climate-related vulnerability metrics of countries, finding that more vulnerable countries pay higher debt costs. Though the specifics of the estimation strategy and the included countries differ, the results in my paper point in a similar direction.

3 Data and Descriptive Statistics

3.1 Sovereign Creditworthiness

I measure sovereign creditworthiness using the Emerging Market Bond Index Global (EMBI) provided by J.P. Morgan. EMBI data has several advantages: Included sovereign bonds are U.S. Dollar-denominated which rules out exchange rate risk. Eligible debt must furthermore have more than one year to maturity and exceed an outstanding face value of $500 million. These features make EMBI data well standardized, liquid and widely-used to track sovereign debt performances of emerging economies.

The start of the EMBI Global at the beginning of 1994 determines my estimation period, which runs from 1994m1 to 2018m12. I collect monthly EMBI Global data for all countries available and calculate month-to-month returns using natural log differences. Positive returns imply improving sovereign creditworthiness.[2] I winsorize the returns at the 1st and 99th percentile to control for outliers. The panel is unbalanced because some countries enter only in later years. As some countries' EMBI series turn temporarily illiquid and hence constant in the index level, I drop all observations with a zero percent EMBI return. To make sure every country in the sample has sufficient variation, I only include those countries with liquid EMBI returns of at least six years (72 months). This criterion is not critical for my results, as shown in a robustness test. The final panel consists of 54 countries and can be found, together with region classifications from Dell et al. (2012), in Table 2. Definition and sources of all variables are in Table 26.

- Table 2 around here -

3.2 Temperature Data

I obtain average monthly temperature data for every panel country since 1901 from the Climate Research Unit (CRU). The data is land-weighted and based on an extensive network of interpolated weather station data (see Harris et al. (2020) for details).[3]

[2] I obtain somewhat stronger results using direct EMBI returns. However, the results also hold when using EMBI spread data as shown in the robustness section. Since both measures are market returns, their interpretation, except for the switched signs, is very similar.

[3] Data is freely available at: `https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/`.

My main variable of interest, as graphically depicted in Figure 1, measures the difference in the observed temperature of a country during 1994m1-2018m12 towards this country's 1901-1950 historical temperature average of that month:

$$HistoricalTempAnomaly_{it} = Temperature_{it} - TempAverage_{i,t(1901-1950)} \tag{1}$$

For instance, temperature in March of 2003 (year-month t) in Argentina (country i) is compared to the temperature of all Marches of Argentina from 1901-1950.

This historical temperature anomaly is a proxy for the degree of global warming witnessed so far. Table 3 listing the summary statistics shows a corresponding mean of 0.842°C for the full sample period. This value approaches the 1°C temperature increase estimated by the IPCC (2018) compared to the pre-industrial age and lies well within their reported confidence range of 0.8°C to 1.2°C. For the sample of temperature anomalies used in the main regressions, the mean is even at 0.896°C. This rise is likely because several countries enter the estimation only in later years, when temperatures increased further.

In line with the assessment of the IPCC (2018) that the 1°C warming experienced so far has already led to impacts on natural and human systems and considering the evidence on the economic effects of temperature fluctuations gathered in Section 2, I interpret $HistoricalTempAnomaly_{it}$ as a measure for warmer than normal periods and extreme weather events. Some statistical confirmation for this perception comes from Table 4, showing that the mean of historical temperature anomalies is higher during periods of heat-related natural disasters such as droughts (0.898), droughts for which there is a damage estimate (0.946), wildfires (0.989) and heat waves (0.988).[4] In addition, I collect stock market data, which is available for 38 out of the 54 sample countries. Table 5 shows that the average temperature anomaly of these sub-sample countries is almost identical to the full sample (0.843). However, temperature anomalies are much lower when the stock market is in upswing (0.785), i.e. stock returns are above the 75th percentile, whereas anomalies are somewhat larger during downturns (0.863), i.e. when returns are below the 25th percentile. Temperature anomalies are thus responsive to both climate- and economy-related news.

[4] Wildfires or heat waves with reported damages also have higher averages but lower number of observation.

I include an additional temperature variable for the main regressions:

$$DeviationAdjustedTempAnomaly_{it} = \frac{HistoricalTempAnomaly_{it}}{StandardDeviation(Temperature_{i,t(1901-1950)})} \quad (2)$$

I divide the anomaly measure by a country's historical standard deviation of monthly temperature. This adjustment is suggested by Dell et al. (2014) and applied, among others, by Barrios et al. (2010). It sets the temperature shock in relation to the usual variation in warm- or coldness of a country. In this way, temperature anomalies in countries with lower seasonality are stronger emphasized.

- Tables 3, 4 and 5 around here -

4 Empirical Framework

Following what Dell et al. (2014) call the "new approach", I estimate an OLS panel regression:

$$\Delta SovereignCreditworthiness_{it} = \beta TemperatureAnomaly_{it} + \delta Precip_{it} + \gamma_i + \gamma_{rt} + \epsilon_{it} \quad (3)$$

Natural log changes in the EMBI index ($\Delta SovereignCreditworthiness_{it}$) are regressed on a temperature anomaly measure and fixed effects. The sample runs from 1994m1 to 2018m12 and consists of 54 countries. Temperature anomalies are either the difference of temperature from its historical average ($HistoricalTempAnomaly_{it}$) or the historical anomaly divided by monthly temperature standard deviation ($DeviationAdjustedTempAnomaly_{it}$) as described in Section 3.2. Based on the gathered evidence, I expect a negative β coefficient. That is, higher temperature anomalies lead to lower sovereign creditworthiness.

I include country fixed effects γ_i to control for time-invariant characteristics such as geography or culture. In addition, year-month fixed effects enter the regression and are interacted with the region classification of a country (γ_{rt}). This approach, suggested among others by Dell et al. (2014), makes sure that common trends, such as shared weather patterns in each region, are controlled for. It ensures that captured temperature shocks are idiosyncratic and local in nature. I apply different fixed effects in the robustness section and find stable results.

Importantly, I do not include any control variables on the country level such as stock returns or exchange rates. This decision is due to the explicit stance of the temperature literature against including any control variable that might be endogenous towards weather and climate variation (Dell et al. (2014), Burke et al. (2015)).[5] Given that stock returns are subject to similar temperature-productivity effects described in Section 2 and also unavailable on a liquid frequency for all panel countries, I abstain from including them. Following leading papers like Dell et al. (2012) and Burke et al. (2015), I only control for precipitation ($Precip_{it}$, also obtained from CRU) and include time-region fixed effects on the highest possible frequency (year-month). Standard errors are clustered on the country level.

Table 8 presents results from several versions of equation (3), including the baseline model. Column (1) introduces the historical temperature anomaly measure and both country and region-time fixed effects, but only on a yearly level. The temperature measure enters negative and statistically significant, but the overall explanatory power of the estimation is quite low. In column (2) I include precipitation on the country level and several international control variables such as changes in the VIX, the US term spread, US corporate risk spread, the 10-year US treasury yield and the returns of a general government bond index. The temperature anomaly coefficient remains negative and statistically significant to this addition. Finally, I estimate the baseline model (column (3)) in which I introduce region times year-month fixed effects, which subsume all non-country specific controls. The explanatory power is now substantially larger, but the temperature anomaly measure is no longer statistically significant. This result might not be surprising, as the literature shows that only particularly affected countries respond to temperature shocks.[6] Precipitation is statistically insignificant in the baseline and all following regressions.

The hypothesis that only affected countries respond to temperature shocks receives confirmation in columns (4) to (6). In these estimations, I repeat the specifications of columns (1)-(3) but replace the historical temperature anomaly with the deviation-adjusted temperature measure ($DeviationAdjustedTempAnomaly_{i,t}$). As described, this version emphasizes temperature shocks in countries with low seasonality. It enters negative and with a stable and strongly statistically significant coefficient (1% level) in all specifications. This result implies that rising temperature leads to a statistically significant decrease of sovereign creditworthiness for countries with low seasonality. Regarding the economic size, an increase of

[5]In their review article on climate and crime, Hsiang et al. (2013) explicitly exclude studies that use a potentially biasing control variable. See also the chapter "bad control" in Angrist & Pischke (2008).

[6]For instance, Dell et al. (2012) also obtain a statistically insignificant baseline effect.

deviation-adjusted temperature anomalies by one standard deviation (0.574°C) leads to a 0.135%-point drop in EMBI returns. This magnitude corresponds to 3.47% of the standard deviation of EMBI returns in the estimation sample. While this effect is modest for now, the next section will investigate the susceptibility of countries towards temperature shocks in greater detail and identify more substantial effects.

- Table 8 around here -

5 Channels

The previous literature established that temperature shocks can be particularly harmful for warmer or poorer countries or affect certain economic sectors like agriculture or industrial production (Burke et al. 2015, Dell et al. 2012). I investigate such channels with respect to their impact on sovereign risk. Specifically, I analyze the general warmness of a country (5.1), its seasonality (5.2), its within year weather fluctuations (5.3), its specialization towards different economic sectors (5.4), the effect of institutions (5.5) and ultimately a combination of all relevant channels (5.6) regarding their temperature-induced sovereign risk impact.

Methodically, I either analyze these channels in an interaction model as follows:

$$\begin{aligned}\Delta SovereignCreditworthiness_{it} =& \lambda_1 TemperatureAnomaly_{it} * Channel_{it} + \lambda_2 Channel_{it} \\ &+ \beta TemperatureAnomaly_{it} + \delta Precip_{it} + \gamma_i + \gamma_{rt} + \epsilon_{it}\end{aligned} \tag{4}$$

That is, the baseline estimation is repeated while $TemperatureAnomaly$ is interacted with the channel of interest, for instance institutional quality. I expect channels that increase the detrimental impact of temperature shocks on sovereign creditworthiness to enter with a negative, while factors that cushion the effect of temperature on sovereign bond performance to carry a positive coefficient sign.

Some of the analyzed channels could be endogenous towards temperature, such as the share of agriculture on the economy. However, as shown by Nizalova & Murtazashvili (2016) and Bun & Harrison (2019) even if one of such channels could be endogenous in the single term, the interacted effect with temperature anomalies can still yield a consistent estimate. This inference holds as long as one of the variables in the interaction term is exogenously determined. This assumption holds plausibly for temperature shocks, as countries can hardly influence their own weather or reallocate because of it. Therefore, even if some channels could be endogenous with respect to temperature, I argue that the interaction terms allow for an unbiased interpretation.

I apply the interaction model for economic variables, as they have a plausibly linear effect on the temperature-sovereign risk relationship. However, some climate-related variables could have non-linear effects that are critical to certain thresholds. For instance, Burke et al. (2015) show that a country's temperature has a non-linear impact on GDP growth. As the interaction model above will only partially capture such non-linear effects, I follow the literature (e.g. Zhang et al. (2018), Graff Zivin & Neidell (2014)) and estimate a bin-model for all climate-related channels:

$$\Delta SovereignCreditworthiness_{it} = \sum_{m} \lambda_m TemperatureAnomaly_{it} * Channel_i^m \\ + TemperatureAnomaly_{it} + \delta Precip_{it} + \gamma_i + \gamma_{rt} + \epsilon_{it} \tag{5}$$

In this way, a country is grouped into one of m (time-invariant) bins. For instance, a country could be sorted into a bin for cold, mild or warm countries based on its average yearly temperature. In order to avoid multicollinearity, one bin has to be omitted in the regression. The estimated coefficient λ_m yields the effect of a temperature anomaly increase of, for instance, the warm country group relative to the omitted reference group, for example the mild countries. Thereby, group-specific non-linear temperature effects are taken into account.

5.1 General Warmness

Figure 3 depicts the histogram of every sample country's 1901-2018 temperature average. There is considerable heterogeneity visible in the warm- and coldness between the coldest (Russia, -4.96°C) and the hottest (Senegal, 28.03°C) country. To investigate if these differences in climatic profiles affect the temperature-sovereign risk relationship, I construct five bins to group every country into: very cold, cold, mild, warm and very warm.

- Figure 3 around here -

I start by grouping according to percentiles: Countries equal to or below the 20th percentile of average annual temperature (from 1901-2018) are classified as "very cold". Countries in the 21st to the 40th percentile of the sample-wide annual temperature distribution are classified as “cold” and so on. Using this data-driven procedure, I make sure that every bin has the same number of countries. Table 6 shows the members of each bin and their mean temperature.

One drawback of this method is that the differences at the end of the distribution are less sharp. “Warm” countries have an average temperature of 24.36°C while “very warm” countries have only marginally hotter climate averaging 26.25°C. Therefore, for a second procedure, I group according to 5°C-intervals: “Very cold” includes countries with mean 1901-2018 temperatures below 10°C, “cold” ranges between 10°C and 15°C, “mild” between 15°C and 20°C, “warm” between 20°C and 25°C and “very warm” above 25°C. With this procedure, the number of countries in each bin varies. Table 7 lists the respective categorization.

- Tables 6 and 7 around here -

I proceed by estimating both bin classifications according to equation (5). I omit the “cold” bin to avoid multicollinearity. Table 9 reports the results and Figures 4 and 5 depict the coefficients. I find that the interaction of the “very warm” category and temperature anomalies is both times negative and statistically significant. As in Burke et al. (2015), warmer countries seem to suffer more from temperature increases than milder tempered countries. For both models, this effect holds with respect to the cold but also the mild and very cold category and for the 5°C-interval model even towards the “warm” category (unreported).

Summing the interaction coefficient of “very warm” countries and the single term coefficient of historical temperature anomalies gives the total size of the effect. For “very warm” countries, I find that a rise in historical temperature anomalies by 1°C, i.e. the estimated global temperature increase since the pre-industrial age, leads to a decline in EMBI returns by 0.432%-points in the percentile- and by 0.464%-points in the 5°C-interval model. These effects correspond to 11.1% or 11.9% of the EMBI returns’ standard deviation in the sample. Consequently, for affected countries, a 2°C warming scenario would lead to falling sovereign creditworthiness in an amount of roughly 25% of the recent EMBI standard deviation. One drawback of the EMBI growth data is that, as a financial market return variable, I cannot attach a dollar value to these effects. Still, the magnitude in terms of percentage points and standard deviation shares is quite substantial. The effect implies sharply rising sovereign borrowing costs for sovereigns that are susceptible to climate change.

- Table 9 and Figures 4 and 5 around here -

5.2 Seasonality

The negative and statistically significant effects of deviation-adjusted temperature anomaly (Table 8, columns (4)-(6)) gave already some confirmation that lower seasonality makes a country more susceptible to temperature socks. The evidence from the recent section corroborates this finding, as countries that are warmer on average tend to have lower seasonality (a country's mean temperature and temperature standard deviation correlate at -0.89).

To test the effects of seasonality on temperature-induced sovereign risk more formally, I group each country into one of five seasonality bins. I again sort according to the quantiles (i.e. five percentile groups) of monthly temperature standard deviation (1901-2018). Table 10 and the depicted coefficients in Figure 6 confirm the previous results: The coefficient for countries with very low seasonality is negative and statistically significant in its interaction with temperature anomalies. The size is nearly identical to that of the warmest country group in the previous section. In addition, countries in the neighboring group of low seasonality have a negative and statistically significant coefficient at the 10% level. In sum, this evidence suggests that hotter countries where seasons hardly vary in terms of warmness are more sensitive towards rising temperature anomalies with respect to their sovereign creditworthiness.

- Table 10 and Figure 6 around here -

5.3 Month and Season Effects

Temperature fluctuations in the previous literature are often on a yearly frequency. I can, instead, exploit the monthly variation in my data to investigate if temperature shocks are different during warmer or colder months. Such a differentiated impact could be plausible: For instance, a warmer summer month could be associated with droughts or declining labor productivity due to extreme heat. On the other hand, a warmer than usual winter month might be beneficial for the economy, as the milder weather lowers heating costs or makes seasonal business cycle fluctuations less severe, for example in the construction sector.

To test these hypotheses, I first re-scale the months of countries in the southern hemisphere to the northern hemisphere classification (that is, the temperature anomaly in Argentina in January is assumed to take place in an adjusted July, February becomes August and so on). I then construct a dummy for each of these adjusted months and repeat the baseline regression by interacting each month with the historical temperature anomaly variable. To avoid multicollinearity, I omit the month May as it usually approaches the annual temperature average. However, results are not critical towards this choice.

Column (1) in Table 11 and Figure 7 show the results of this exercise. There seems to be no pattern that would confirm the hypothesis of more severe temperature shocks in summer months. Some months approach statistical significance at the 10% level, however, such findings are not stable and in general sensitive to the omitted base category. For instance, in column (2) I omit December to see potential summer-effects more directly, which leads to changes in signs and significance levels for several coefficients.

Lastly, I interact temperature anomaly shocks with the respective season. This specification does not require a re-scaling of months in southern hemisphere countries (e.g. summer is June-August in northern and December-February in southern hemisphere). Choosing autumn as a base, column (3) of Table 11 and Figure 8 demonstrate once again that there seem to be no statistically significant effects during certain seasons regarding the temperature-sovereign risk relationship. These results lead to the conclusion that overall country warmness rather than within year temperature variation is what matters for the temperatures sensitivity of a country's sovereign creditworthiness.

- Table 11 and Figures 7 and 8 around here -

5.4 Economic Sector Specialization

In the following, I investigate if countries that are specialized in certain economic sectors are more susceptible towards temperature deviating positively from its historical average. For instance, Auffhammer & Schlenker (2014) summarize empirical studies on the tight relationship between agricultural production, weather outcomes and climate change. Furthermore, the literature linking temperature and labor productivity typically looks at manufacturing and industrial sectors (Cachon et al. 2012, Zhang et al. 2018). Lastly, countries specialized into commodity and in particular fossil-fuel sectors could see their sovereign creditworthiness deteriorate because these industries might no longer have viable business models as climate change intensifies (ECB 2019).

To analyze these channels, I interact the temperature anomaly variable as described in equation (4) with measures for industry specialization. Though pure temperature anomalies are the primary interest of this specification, I also run the regressions using the deviation-adjusted anomaly measure. This addition is because the variable emphasizes countries with lower seasonality and warmer weather, which were shown to be important characteristics for the temperature-sovereign relationship.

Table 12 shows the results for agricultural specialization. I interact separately with the land share devoted to agriculture in relation to a country's total land area, the GDP share of agriculture and the share of employees working in the agricultural sector in relation to total employment. Negative interaction effects would indicate that higher agricultural specialization leads to more detrimental temperature impacts on sovereign creditworthiness. However, while all coefficients of the interactions with temperature anomaly are negative in sign, none of them are statistically significant at conventional levels. The evidence that larger agricultural sectors differentiate temperature shock impacts is therefore weak at best.

Next, I interact with specializations in the manufacturing sector, which is captured by the GDP share of manufacturing and the employment share of the industrial sector.[7] The results in Table 13 also include interactions with the employment and the GDP share of the service sector and the total share of oil, gas, coal, mineral and forest rents in relation to GDP (ResourceRentsToGDP). However, there are once again no statistically significant interaction effects for either one of the temperature anomaly variables. Of course, it could still be the case that fossil industries captured in the resource-rent variable will come under stronger pressure in future years and thereby endanger the creditworthiness of their sovereign. Still, such effects seem to be either weak during my estimation period or not connected to the temperature shocks estimated in the model. Overall, the gathered evidence does not suggest that countries which are specialized in a certain economic sector are more (or less) susceptible to temperature increases with respect to their sovereign solvency.

- Tables 12 and 13 around here -

5.5 Institutions

The subsequent section investigates if the quality of a country's institutions differentiates the effect of temperature increases on sovereign risk. Better institutions make sure that countries

[7] There is no data series for the employment share in manufacturing, but I expect industrial sector employment shares to be closely correlated.

have a stable political and business environment, low corruption, accountable political leaders and a government that can mobilize investments, provide common goods and respond to market failures or natural disasters. All these factors matter in the context of climate change, for instance if droughts or floods lead to physical damages that require swift government intervention, or if distributional consequences of temperature-induced costs and losses need to be managed efficiently. In sum, better institutional quality could make a country more resilient to the various challenges global warming poses for emerging economies.

In order to capture several features of institutional quality, I interact both temperature anomaly versions with a range of institutional measures. My main interest lies once again in the raw temperature anomaly measure as it proxies global warming directly and is more straightforward to interpret, but I will also post results for the deviation-adjusted version. The first set of interactions are with the World Bank's institutional measures for the quality of a country's rule of law (Table 14, columns (1)-(2)) and its control of corruption (columns (3)-(4)) which capture most of all business and legal aspects of institutions. I continue with interactions measuring the impact of political rights (columns (5)-(6)) and civil liberties (columns (7)-(8)) by Freedom House to see if free elections, freedom of speech and other politically- and societal-related aspects play a role. Next, I analyze the amount of income redistribution from before to after taxes (Table 15, columns (1)-(2)) from Solt (2019) to see if more equitable countries that redistribute a larger share of their income, thereby potentially taxing elites and lowering poverty, react different to temperature shocks. Lastly, I use the Polity2 index (columns (3)-(4)) and its components from the Center for Systemic Peace that show which governments are more democratic (columns (5)-(6)) and hence less authoritarian (columns (7)-(8)).

Simply put, I find strong and robust evidence for all of these channels. Interactions with institutional variables for which higher values indicate better quality (rule of law, control of corruption, income redistribution, polity2, democratic governments) enter with positive, while measures which are indexed so that higher values imply lower quality (civil liberties, political rights, authoritarian governments) carry negative signs in all cases. For the pure temperature anomaly measure, all interactions are at statistical significance levels of 1% or 5%. In the case of the deviation-adjusted measure, the coefficients are slightly weaker in significance but significant at conventional levels except for the income redistribution interaction.

- Tables 14 and 15 around here -

I expand the analysis to investigate if the results also hold for climate-related institutions. To this end, I draw data from the Notre Dame Global Adaption Initiative, which publishes the Notre Dame Global Adaption Index (ND-GAIN). This index takes both the climate-related adaptive readiness of a country as well as its physical and institutional vulnerability towards global warming into account. For instance, the index covers the economic, governance and social-related institutions of a country that can provide resilience towards damages from climate change. The vulnerability component measures physical and topographical exposure risks and the dependency on climate-sensitive sectors.

Column (1) of Table 16 reports the results of the overall ND-GAIN interacted with temperature anomalies. I obtain a positive coefficient that is statistically significant at the 5% level, indicating that countries with stronger climate-related institutions suffer significantly less from rising temperature than less well-prepared countries. Results for the interaction between ND-GAIN and the deviation-adjusted temperature are not statistically significant, however, the margin plot in Figure 9 provides notable confirmation that countries with lower ND-GAIN scores suffer significant negative temperature shocks on their sovereign creditworthiness, whereas the effect becomes statistically insignificant for higher ND-GAIN levels.

Interactions with the readiness component (columns (3)-(4)) and the vulnerability component (columns (5)-(6)) of the ND-GAIN index reveal that the readiness part is driving the results. The corresponding interactions are statistically significant at the 1% level, while the vulnerability interactions are statistically insignificant. This finding is in line with previous results, as the vulnerability component measures the dependency on climate-vulnerable sectors, which were shown to be unrelated to the temperature-sovereign risk relationship in the previous section. On the other hand, the readiness component captures climate-related governance factors that correlate positively with the previous measures of institutional quality.

In sum, this section provides robust evidence that institutions strongly influence the relationship between rising temperature and sovereign creditworthiness. Countries with lower institutional quality, both in a traditional and in a climate-related context, have so far been hit significantly harder by temperature deviating from its historical levels. This result could suggest that better institutions can make a country more resilient towards the physical damages from climate change. As future global warming will lead to growing damages, transition costs and distributional issues, having stronger institutions to manage these challenges could be a viable strategy in the adaption process towards climate change.

- Table 16 and Figure 9 around here -

5.6 Combining relevant Channels

A channel that could be related to the impact of institutional quality is economic development. Therefore, I interact temperature anomalies with a country's GDP per capita. Column (1) in Table 17 confirms that the level of economic development matters, in that poorer countries' sovereign creditworthiness is statistically significantly stronger damaged by a temperature shock than those of economically more developed countries.

However, it could be the case that poorer countries have larger susceptibility to rising temperature because they tend to have worse institutions. It could also be the other way around, and the effect of worse institutions only works through the associated lower level of economic development. More broadly, the vulnerability of the warmest countries uncovered in Section 5.1 could also be interrelated with institutions and development. For instance, Easterly & Levine (2003) show that countries in tropical climate zones tend to develop worse institutions which lowers their economic progress (see also Sachs (2001)). Indeed, annual average temperatures and the rule of law index correlate negatively in the sample (-0.165), indicating that warmer countries tend to have worse institutions.

A possible, if not perfect way to test which channels ultimately matter for the temperature-sovereign relationship is to combine all relevant interactions in a single model. I start by adding the interaction of temperature anomalies and the rule of law index, as one of the institutional variables (results also hold for other measures), to the model with interacted GDP per capita (column (2)). While the interaction coefficient for rule of law remains statistically significant and of similar size than in Table 14, the GDP per capita interaction with temperature decreases in size and becomes statistically insignificant. This finding provides some confirmation that the effect of lower economic development on the temperature-sovereign relationship is mostly driven by the fact that poorer countries tend to have worse institutions.

In column (3), I add the deviation-adjusted temperature variable to the specification of column (2). So far, this variable has always been statistically significant, likely because it emphasizes temperature shocks in warmer and less seasonal countries. The variable remains negative and statistically significant in column (3), but the interacted rule of law coefficient also stays stable and significant. GDP per capita remains statistically insignificant. This result suggests that, even after controlling for temperature shocks in warmer countries, institutional quality can still cushion the impact of a temperature shock to a significant degree. This finding is confirmed in column (4) in which I replace the deviation-adjusted temperature measure with the five bins representing very cold, cold, mild, warm and very warm countries according to 5°C-intervals. Leaving out the cold country bin, I find that both the interaction of temperature anomaly with the very warm country bin and with the rule of law index continue to stay statistically significant and similar in size than before.

While the long-run effects of climate on institutional development are difficult to entangle and beyond the scope of this paper, the fact that the impact of institutions on the temperature-sovereign relationship continues to hold even after controlling for the warmness of country shows that the institution-channel does not work purely through the climate-channel. In that sense, policy makers, independent of the warmness of their country, have an incentive to improve institutional quality, as it can cushion the impact of rising temperatures on their sovereign risk level.

- Table 17 around here -

6 Robustness Tests

6.1 Changing the Fixed Effects Specification

In order to conduct robustness checks, I repeat those specifications that yielded the most decisive results in the previous sections. These include the deviation-adjusted temperature variable (Table 8, column (6)), the bin-regression analyzing the warmness of countries using 5°C-intervals (Table 9, column (2)) and the interaction with institutional characteristics from which I choose the rule of law index (Table 14, column (1), results also hold for other institutional variables). For the bin-regression, I omit the "cold" country category because it provides a distinctive comparison group to the "very warm" country group. However, results also hold for omitting other groups for the majority of robustness checks. More importantly, I am interested in the total effect of the "very warm" country group interaction, which is independent of the omitted bin.

I start by changing the fixed effects setting for each of these three specifications. First, I deconstruct the interaction of region and year-month fixed effects and instead only include year-month time effects, thus omitting the regional component (Table 18, columns (1)-(3)). Second, I re-include the region times month-year effects and in addition interact the country fixed effects with a year time fixed effect (columns (4)-(6)). Though I am not aware of a paper in the relevant literature using such a country-year effect, the interaction controls for time-fixed differences between countries within each year. Lastly, I control for region times month-year and additional country times quarter fixed effects (columns (7)-(9)). The latter interaction absorbs seasonal differences that vary over each quarter.

In sum, the main results of the paper stay intact for each of these modifications. Dropping the region fixed effects only marginally changes the coefficients. The country by year fixed effects, in contrast, reduce the statistical significance of the deviation-adjusted temperature anomaly to the 10% level, and also lower the total effect of very warm countries from -0.464 in the baseline to -0.320 in column (5). Still, this specification is unusual in the literature and the overall direction of the results is the same as before. Interacting the country with quarter fixed effects yields stable and even slightly stronger results than in the baseline.

- Table 18 around here -

6.2 Changing the Dependent Variable

Next, I test if the main results hold when using a different dependent variable. All specifications so far used monthly returns of the EMBI index. A natural alternative for this measure are differences in the EMBI spread instead of the index level.

Table 19 repeats the three main regressions using monthly first differences of EMBI spreads as the dependent variable (columns (1)-(3)). All results continue to stay statistically significant, if on somewhat lower levels. The coefficient signs are now reversed as rising EMBI spread changes indicate lower sovereign creditworthiness. Regarding the economic magnitude, an increase of 1°C of the anomaly measure in "very warm" countries leads to a 9.62-point increase in EMBI spread changes. This effect is 11.98% of the overall EMBI spread change standard deviation (80.34) and thus extremely close to the 11.9% obtained for the EMBI index returns.

In order to investigate the validity of the results for a different variable than the EMBIs, I collect sovereign CDS data. However, this data is only available since roughly 2008 and only for 37 of the 54 panel countries. With these limitations in mind, I construct changes in the CDS spread the same way as with the EMBI spread, i.e. I take first differences, set zero returns to missing and winsorize at the 1st and 99th percentile. I use CDS spread changes as a new dependent variable in columns (4)-(5). I do not report the regression using the temperature bin interactions because the grouping process is significantly biased due to the lower number of countries (though the results point in a similar direction as before). The interaction with the rule of law index is negative and statistically significant at the 5% level, which corroborates the previous results. The deviation-adjusted measure enters positively but is not statistically significant. However, the imprecise estimation could likely be due to the lower number of observations, since the coefficient size is still large. An increase of deviation-adjusted temperature by one standard deviation of the estimation sample (0.627) increases CDS changes by 5.19 points which is 7.3% of the CDS standard deviation (71.05).

- Table 19 around here -

6.3 Changing the Lag Structure

Dell et al. (2012) include up to ten years of lagged temperature shocks into one of their specifications. Though their effects appear to be driven by contemporaneous temperature fluctuations, I also extend my model with twelve months of lagged temperature anomalies.

However, columns (1)-(3) in Table 20 reveal that, similar to Dell et al. (2012), contemporaneous shocks are driving the results. In column (1), the current level of deviation-adjusted temperature remains negative and statistically significant while all its lags are statistically insignificant and without a clear trend. In column (2), I interact every temperature bin-category with the temperature anomaly variable and each of its twelve legs (yielding 52 interaction terms). Table 20 only shows the interaction of the "very warm" category and contemporaneous temperature to save space. The "very warm" country bin still has a negative and significant interaction effect, though the significance is slightly lower likely because of the numerous additional interactions. Lagged interactions are again quite noisy and in almost all cases not statistically significant (not reported). Column (3) interacts the rule of law index with the twelve lags of temperature anomaly but the non-lagged version remains the only significant coefficient.

- Table 20 around here -

6.4 Changing the Historical Temperature Average Period

All main specifications have used 1901-1950 as a historical period to build temperature averages over, from which deviations were calculated. I chose 1950 because it is long enough to ensure a representable average (compared to 1930 or 1940) but with sufficient distance to global temperatures starting to increase more measurably (such as 1960 or 1970).

In Tables 21 and 22, I repeat all three main estimations using 1930, 1940, 1960 or 1970 as endpoints for the historical average period. All coefficients of interest hardly change as a consequence of these adjusted average periods, including the total effect of temperature anomalies in "very warm" countries.

- Tables 21 and 22 around here -

6.5 Dropping Countries with lower Data Coverage and larger Landmass

In the main specification, I included all countries with liquid EMBI return data of at least six years. I chose this criterion to manage the trade-off between having a large panel and sufficient observations for each country in the sample. In columns (1)-(3) of Table 23, I set the inclusion criterion to ten years (120 months) of liquid EMBI return data. 15 countries in the original sample are affected by this requirement (Angola, Azerbaijan, Belarus, Bolivia, Costa Rica, Guatemala, India, Jordan, Latvia, Lithuania, Mongolia, Namibia, Romania, Senegal, Zambia). I drop these countries and repeat the three main regressions. The number of observations only decreases slightly as a result of this adjustment, and all the main effects retain their statistical significance. The effect of temperature increases in the warmest countries even rises somewhat, in both magnitude and significance.

One further concern I address deals with countries covering a huge landmass. Nations like Russia or China could have several climate zones which makes their temperature average only a rough measure for weather fluctuations. Therefore, I drop the ten countries with the largest landmass from my sample (Russia, China, Brazil, India, Argentina, Kazakhstan, Mexico, Indonesia, Mongolia, Peru) and repeat the main regressions. Columns (4)-(6) reveal that the number of observations now decreases more notably. However, the main results remain broadly intact. Deviation-adjusted temperature shocks even increase, as does the interacted effect of institutions and temperature anomalies. The "very warm" country bin is now marginally insignificant just before the 10% level, perhaps because of the lower number of observations or the changing number of countries in each bin. Still, the total effect of this group still has the same size as in the main regression (-0.443).

- Table 23 around here -

6.6 Other Temperature Anomaly Measures

I construct one further measure to detect weather anomaly shocks. This variable is inspired by the fact that not only increases in temperature levels but also in variability are verified as one of the detrimental impacts of climate change (Bathiany et al. 2018). I take the standard deviation of monthly temperature over 12-month rolling windows for every country. This variable captures the volatility of weather over the previous year. I subtract from this measure a country's temperature standard deviation from 1901 to 1950. In this way, similar to the historical temperature anomaly measure, I capture deviations of temperature volatility above its pre-global warming average (HistoricalDeviationAnomaly).

Table 24 presents the results for this variable. The historical change in temperature standard deviation is negative and statistically significant as a single variable (column (1)). Its size is similar to the deviation-adjusted temperature shocks, which suggests that periods of more volatile weather can hurt sovereign creditworthiness. However, the interaction coefficients of the variable with both institutional quality and the warmest countries are statistically insignificant (columns (2)-(3)). Though the point estimates are actually comparable to the main regressions or even larger, the effects are imprecisely estimated. This result could suggest that more volatile weather hurts all countries' sovereign bond performance, independent of their climate zone or institutional framework.

- Table 24 around here -

6.7 Testing for Transition Risks

Though it is, as described in Section 2, extremely difficult to differentiate between physical and transition risks in the temperature literature, I conduct a test that could possibly detect transition risks. To this end, I use the Paris Climate Agreement, which was sealed in December 2015, as a transition shock. With the Paris Agreement, almost all countries in the world agreed to limit global warming to well below 2°C. If temperature increases also feature a transition risk component, it could be the case that temperature shocks have stronger impacts on sovereign creditworthiness since the Paris Agreement, because investors are more sensitive towards climate issues.

To test this channel, I interact the three main regressions as well as raw temperature anomalies with a time dummy for the Paris Agreement that is 1 after December 2015. For the temperature anomaly and the deviation-adjusted temperature measure, the Paris dummy does not differentiate the impact of these variables, as the interaction effects are statistically insignificant (Table 25, columns (1)-(2)). The results are similar for "very warm" countries and institutions (columns (3)-(4)): The double interaction of temperature and rule of law remains statistically significant and comparable to previous results, whereas the triple interaction with the Paris dummy is small and statistically insignificant. Although this is no definitive result, it could suggest that temperature shocks are first and foremost a physical risk source, which is largely independent of climate agreements or transition risks.

- Table 25 around here -

7 Conclusion

I extend the literature on temperature fluctuations to finance, specifically the sovereign debt performance of emerging economies. To this end, I collect monthly temperature data since 1901 for 54 emerging countries. For each country, I calculate the temperature deviation of every month from this month's 1901-1950 temperature average. I run my main empirical analysis from 1994m1 to 2018m12, up until this temperature anomaly is on average 0.84°C, reflecting past climate change trends. In line with previous literature, I argue that rising temperature deviations approximate physical weather and climate damages.

I regress Emerging-Market-Bond-Index returns on temperature anomalies while controlling for established country, time and region fixed-effects. My main result is that the effects of temperature anomalies on the cost of sovereign debt critically hinge on conditioning factors. Temperature deviations lower sovereign bond performance (i.e. increase sovereign risk) significantly for countries that are (i) warmer on average, (ii) less seasonal, (iii) and have lower institutional quality, both in terms of traditional- and climate-related metrics. Importantly, the effects of institutional quality and the warmness of a country on the temperature-sovereign risk relationship hold simultaneously, which implies that stronger institutions can improve the resilience of a country towards climate change, independent of its climatic profile.

The economic effects of temperature increases are more than noteworthy. According to my analysis, if a country with an average annual temperature above 25°C faces a 1°C increase in monthly temperature compared to its historical mean, its EMBI returns are lowered by 0.464 percentage points on average. This effect corresponds to 11.9% of the EMBI returns' overall standard deviation. Hence, a 2°C global warming scenario could lower EMBI returns of affected countries by roughly a quarter of their overall standard deviation.

This magnitude suggests that, in the absence of climate-adaption strategies, affected countries likely face considerable increases in their sovereign borrowing costs if temperatures continue to rise due to climate change. These results also raise distributional questions: As of 2017, the countries in my panel were responsible for just 36.6% of accumulated historical global CO_2 emissions but posed 66.2% of the global population. Policy action to limit the degree of global warming and to build adaptive capacities through stronger institutional frameworks are therefore called for.

8 References

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9 Tables and Figures

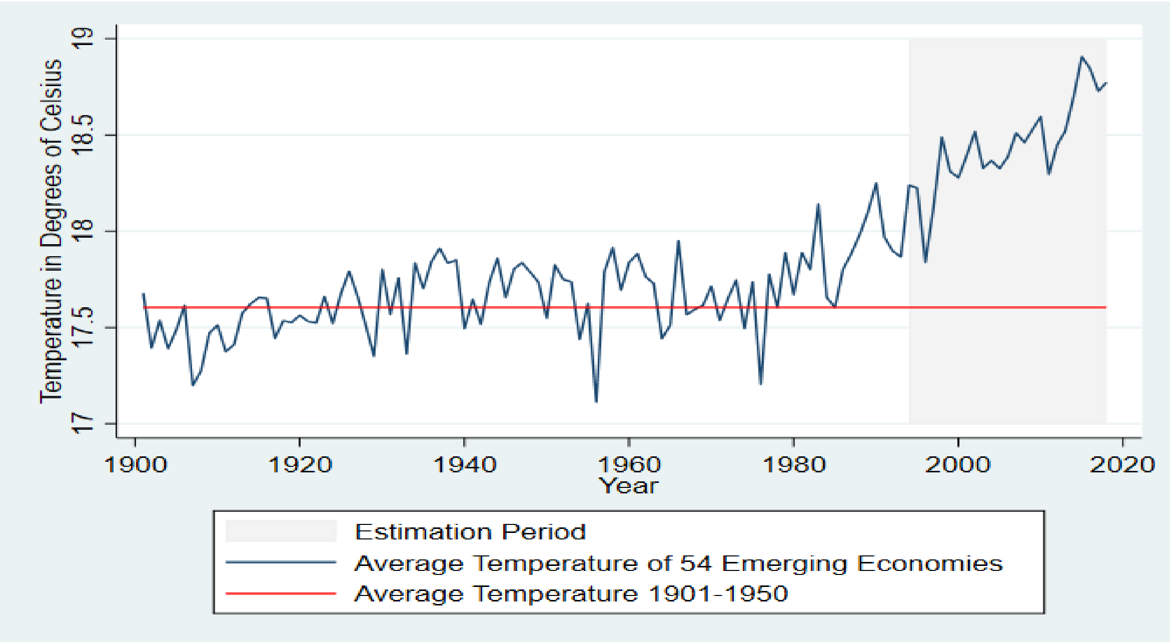

Figure 1: Average annual temperature of 54 emerging economies in the sample from 1901-2018 and 1901-1950 temperature average.

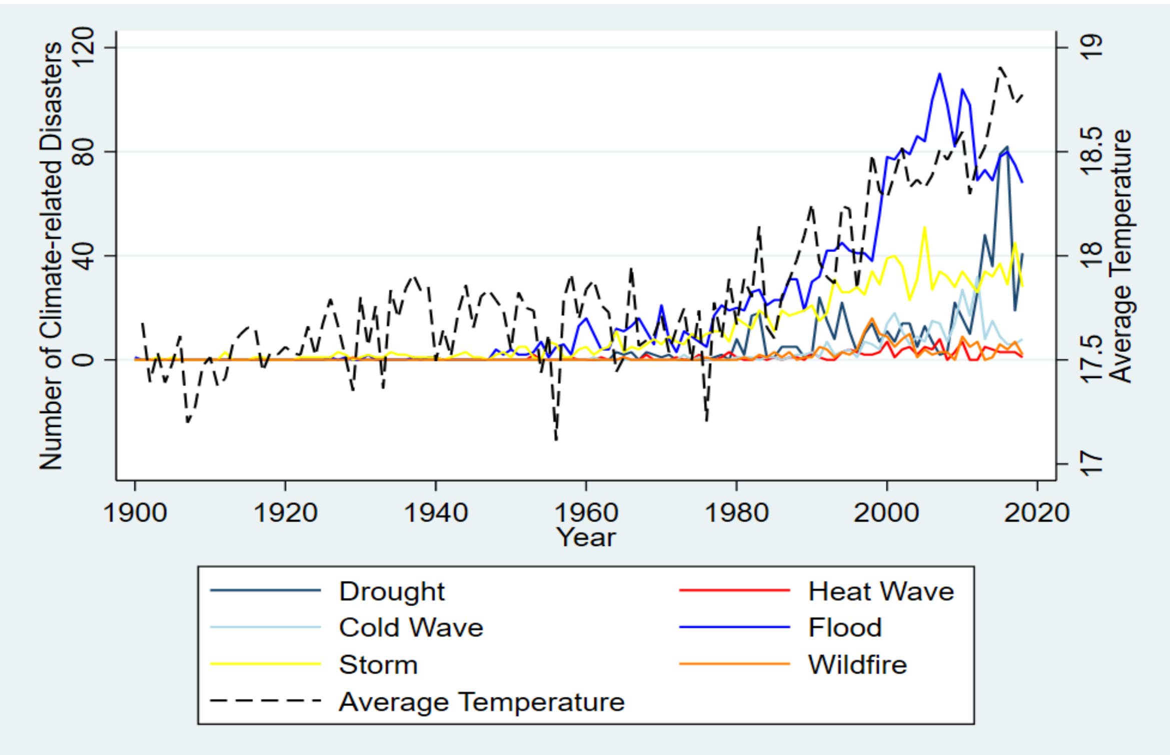

Figure 2: Number of climate-related natural disasters and average temperature of panel countries.

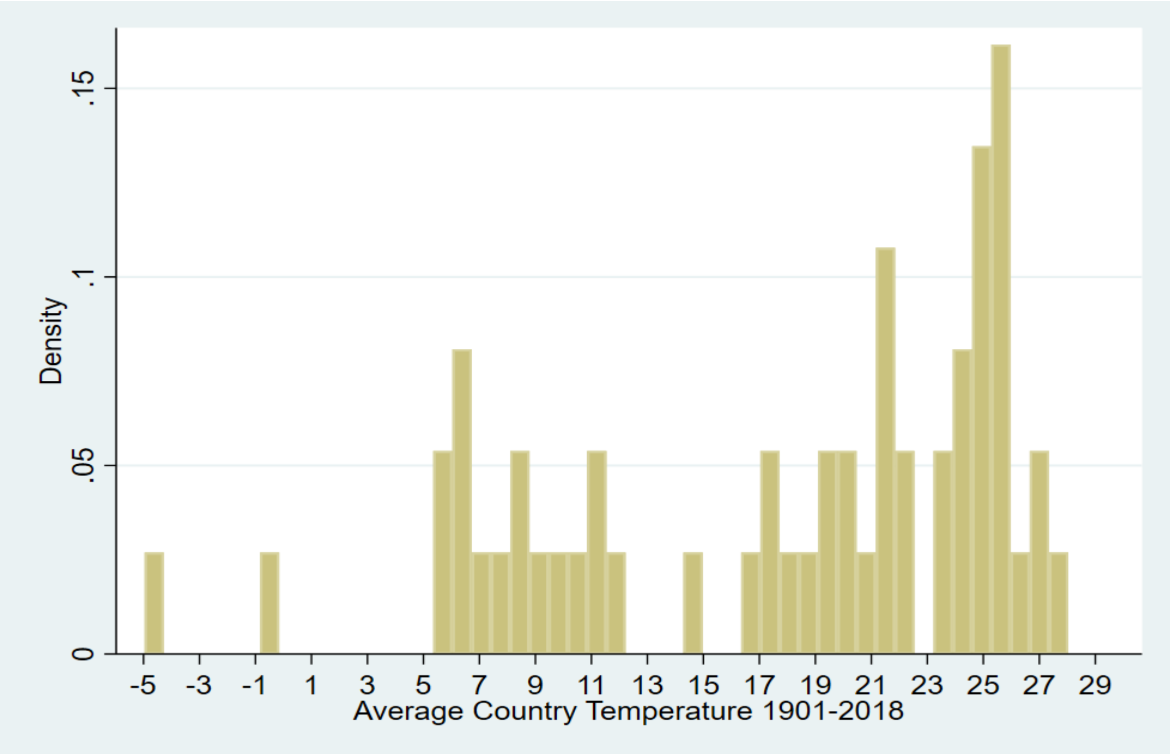

Figure 3: Histogram of average temperature of every sample country.

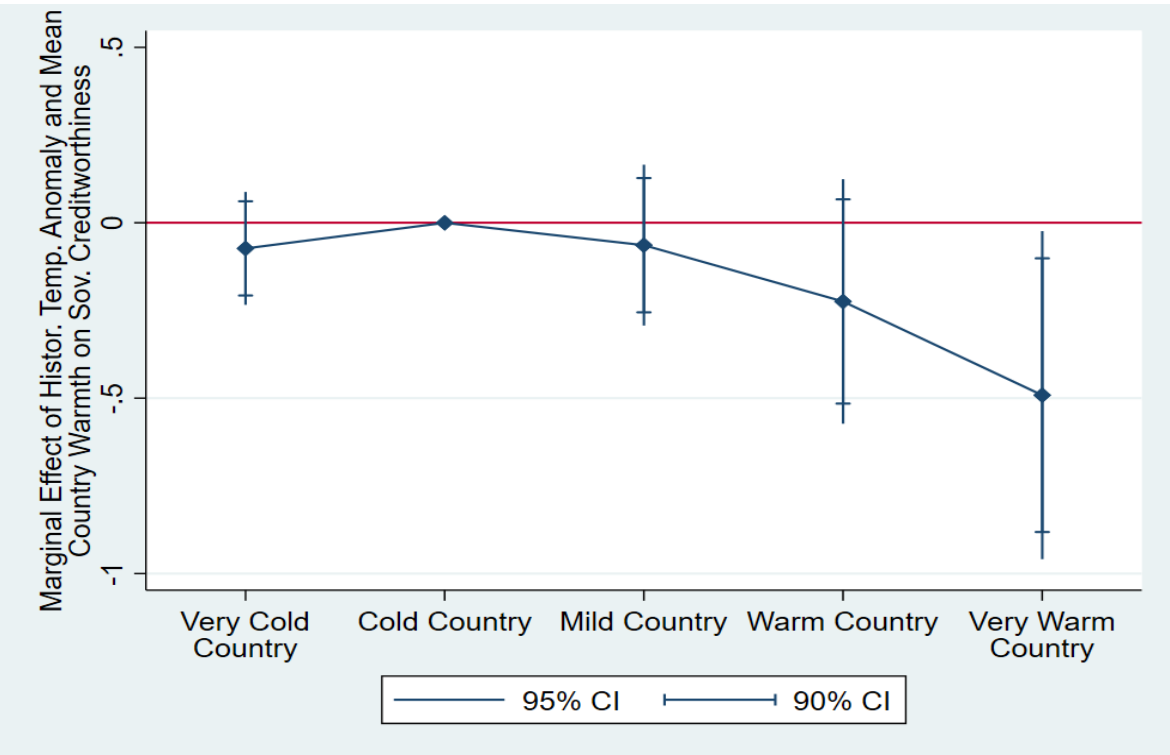

Figure 4: Coefficients estimated in Table 9 for climatic bins according to percentiles of average temperature.

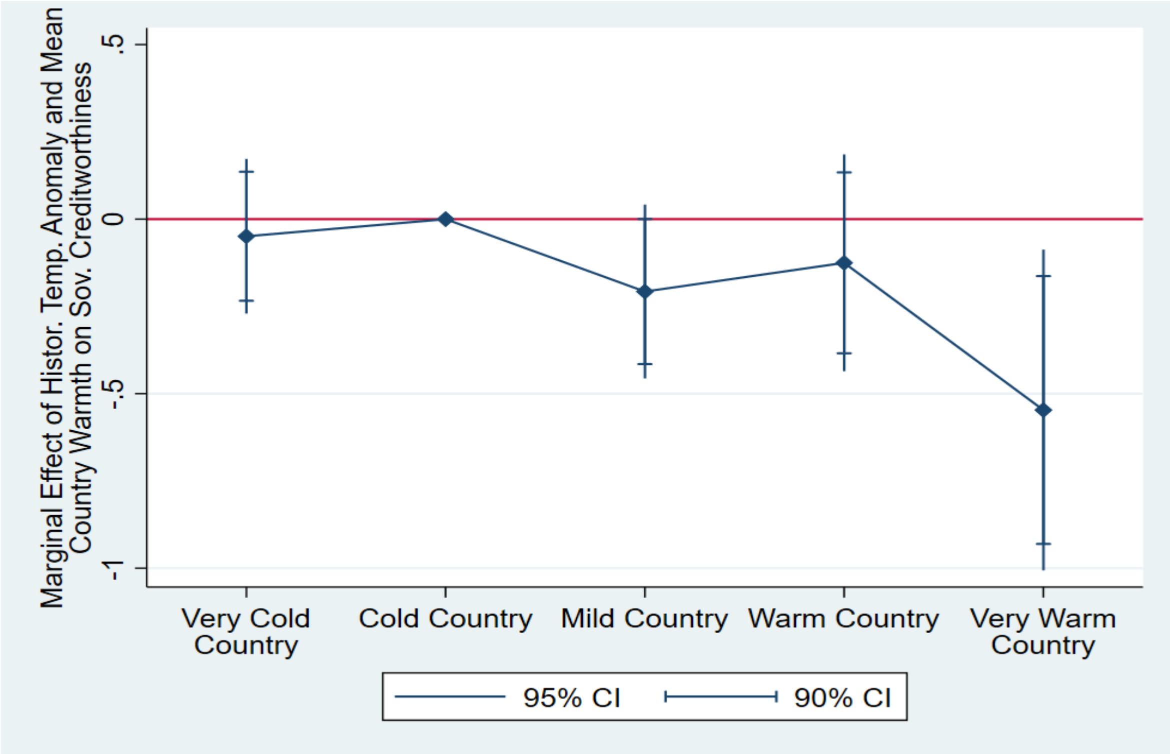

Figure 5: Coefficients estimated in Table 9 for climatic bins according to 5°C-intervals of average temperature.

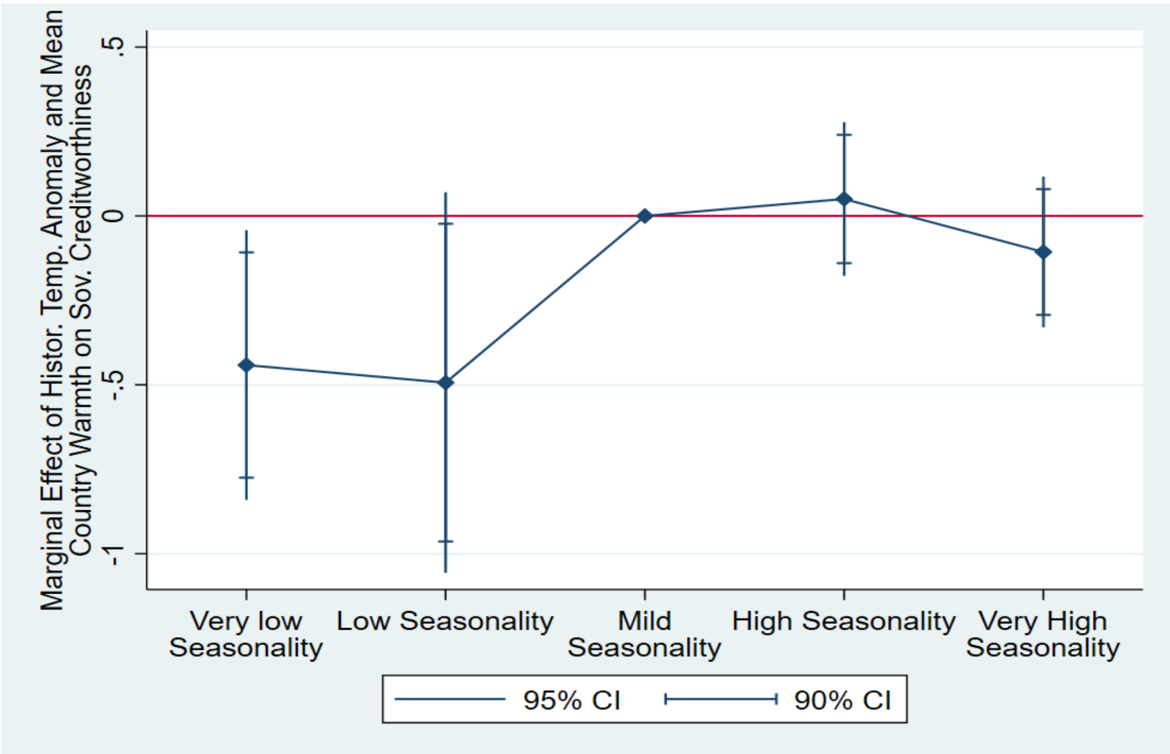

Figure 6: Coefficients estimated in Table 10 for bins according to percentiles of monthly temperature standard deviation (1901-2018).

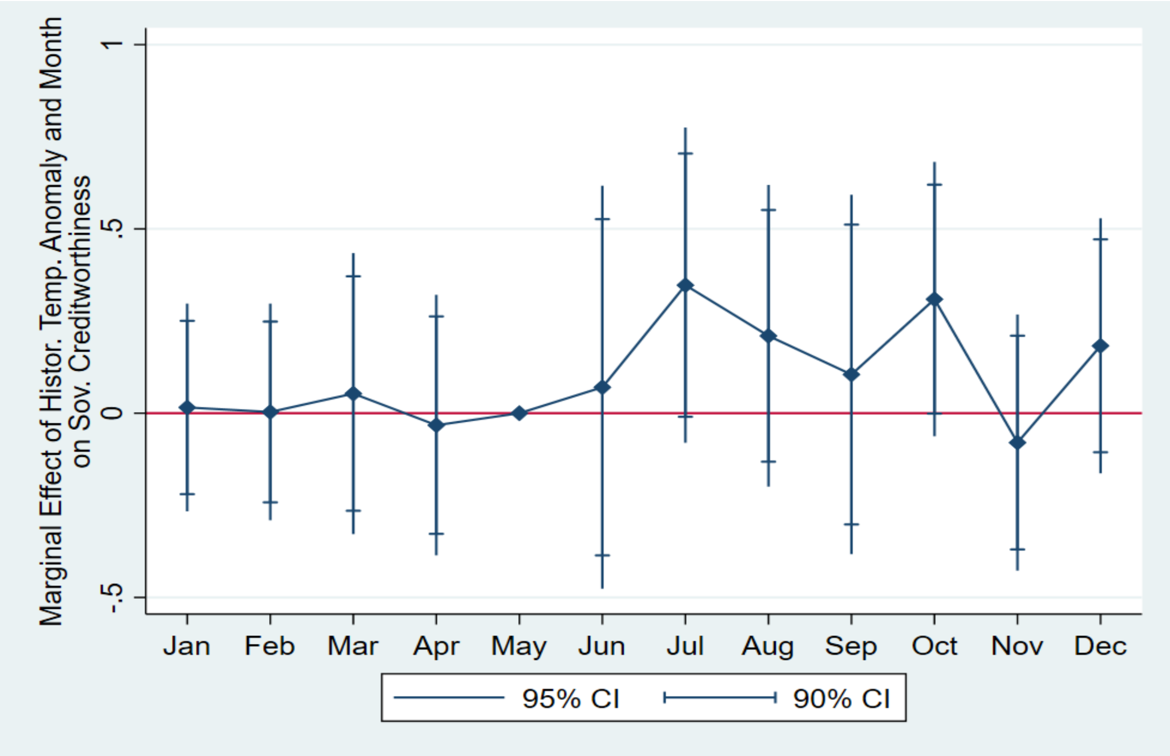

Figure 7: Coefficients estimated in Table 11 column (1) for month effects (adjusted for southern hemisphere).

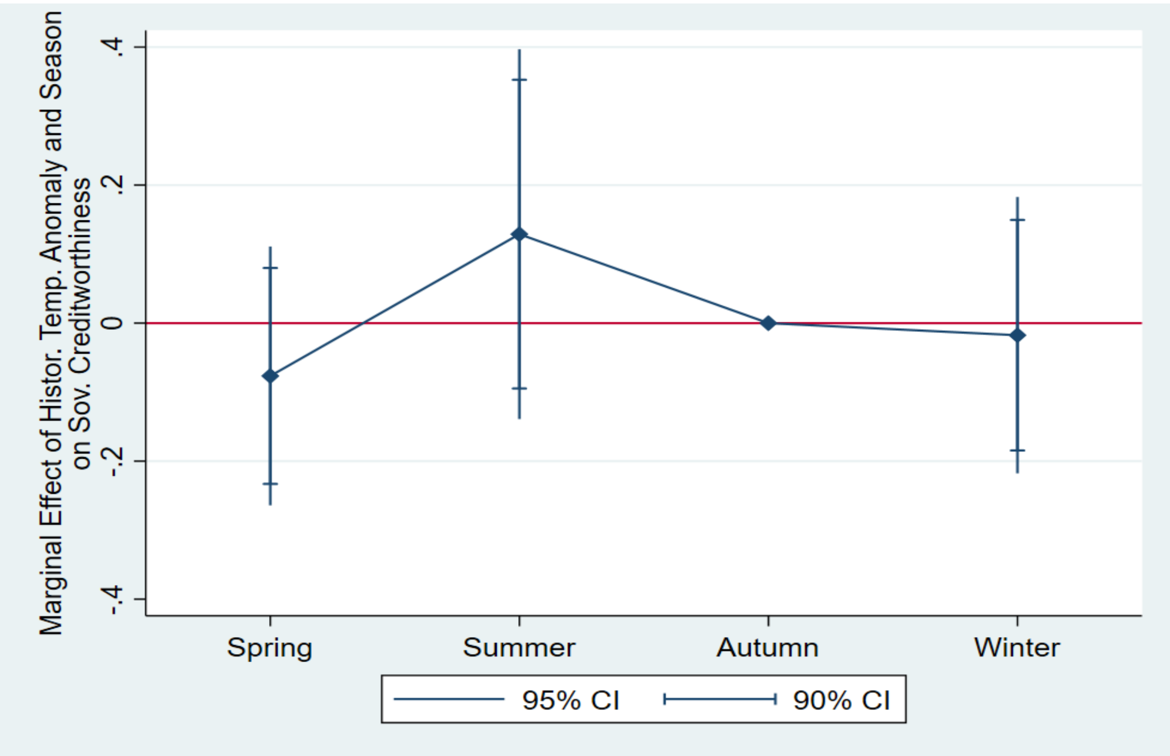

Figure 8: Coefficients estimated in Table 11 column (3) for season effects.

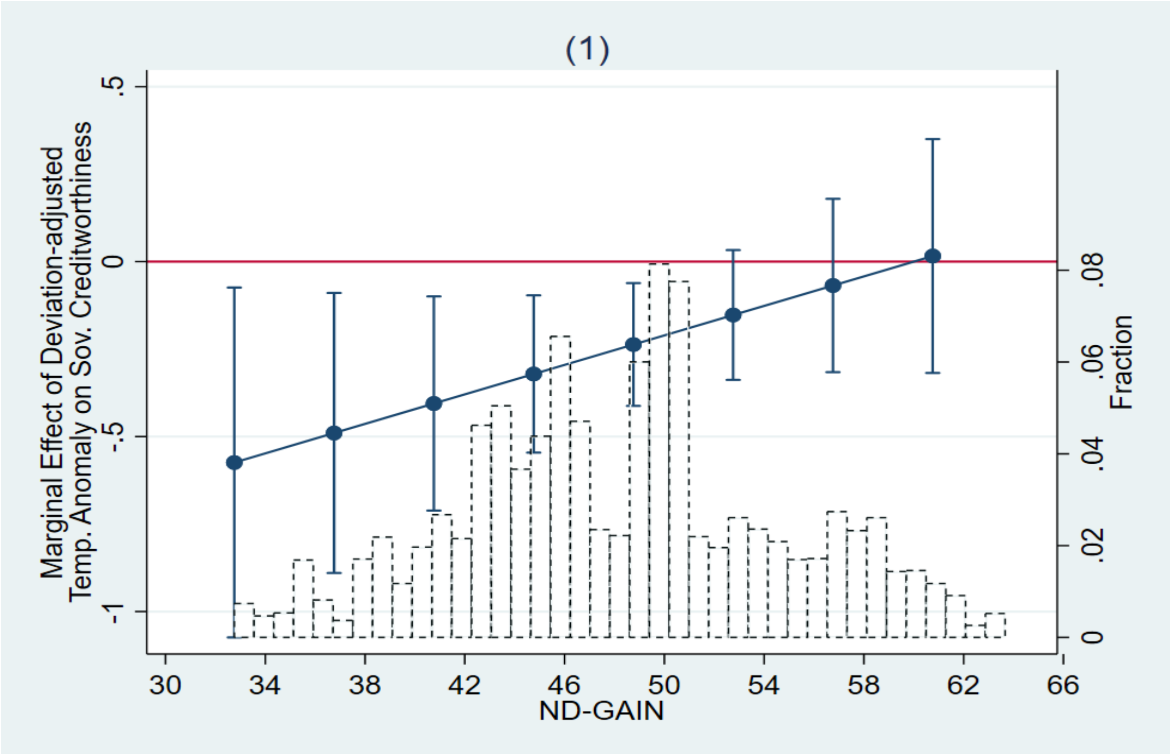

Figure 9: Marginal effect of deviation-adjusted temperature increases interacted with ND-GAIN index. Bars indicate 95% confidence intervals. Corresponding regressions are in Table 16.

Table 1: Distinction between physical and transition climate change risks. Source: Bank of England (2018).

Risk Type	Implications for Credit	Implications for Markets	Implications for Business
Physical	Increasing flood risk to mortgage portfolios; declining agricultural output; increasing default rates	Severe weather events can lead to re-pricing of sovereign debt	Severe weather events can impact business continuity
Transition	Tightening efficiency standards impact property exposures; stranded assets impair loan portfolios; disruptive technology leads to auto finance losses	Tightening climate-related policy leads to re-pricing of securities and derivatives	Changing sentiment on climate issues leads to reputational risks

Table 2: List of included countries and region classification

Region	Countries
Asia-Pacific	China, India, Indonesia, Malaysia, Mongolia, Pakistan, Philippines, Vietnam
Eastern Europe & Central Asia	Azerbaijan, Belarus, Croatia, Georgia, Hungary, Kazakhstan, Latvia, Lithuania, Poland, Romania, Russia, Serbia, Ukraine
Latin America & Caribbean	Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Jamaica, Mexico, Panama, Peru, Uruguay, Venezuela
Middle East & North Africa	Egypt, Iraq, Jordan, Lebanon, Morocco, Tunisia, Turkey
Sub-Sahara Africa	Angola, Gabon, Ghana, Ivory Coast, Namibia, Nigeria, Senegal, South Africa, Zambia

Table 3: Summary statistics

	N	mean	p50	sd	min	max
ΔEMBI	10,006	0.686	0.729	3.921	-16.23	13.47
ΔEMBI (regression sample)	9,957	0.691	0.729	3.898	-16.23	13.47
HistoricalTempAnomaly	16,200	0.842	0.694	1.190	-5.514	8.830
HistoricalTempAnomaly (regression sample)	9,957	0.896	0.742	1.129	-5.254	8.830
DeviationAdjustedTempAnomaly	16,200	0.355	0.223	0.514	-1.627	4.007
DeviationAdjustedTempAnomaly (regression sample)	9,957	0.418	0.257	0.574	-1.627	4.007

Table 4: Mean temperature anomaly measure during natural disaster periods

	Full Sample Mean	Drought	Droughts with reported Damage	Wildfire	Heat Wave	Cold Wave or severe Winter
Historical TempAnomaly	0.842	0.898	0.946	0.989	0.988	0.0623

Table 5: Mean temperature anomaly measure during stock market upswings and downswings (stock data available for 38 countries)

	Sub-Sample Mean (of countries that report stock returns)	Stock market returns > 75th percentile	Stock market returns < 25th percentile
Historical TempAnomaly	0.843	0.785	0.863

Table 6: Countries in each percentile-defined climatic bin

	Very Cold	Cold	Mild	Warm	Very Warm
	Belarus	Argentina	Angola	Brazil	Belize
	Chile	Azerbaijan	Bolivia	Colombia	Ghana
	China	Croatia	Ecuador	Costa Rica	Indonesia
	Georgia	Hungary	Iraq	Dominican Republic	Ivory Coast
	Kazakhstan	Lebanon	Jordan	Egypt	Malaysia
	Latvia	Morocco	Mexico	El Salvador	Nigeria
	Lithuania	Romania	Namibia	Gabon	Panama
	Mongolia	Serbia	Pakistan	Guatemala	Philippines
	Poland	South Africa	Peru	India	Senegal
	Russia	Turkey	Tunisia	Jamaica	Venezuela
	Ukraine	Uruguay	Zambia	Vietnam	
Average 1901-2018 annual temperature	5.198°C	13.439°C	20.666°C	24.362°C	26.256°C

Table 7: Countries in each 5°C-interval-defined climatic bin

	Very Cold: ≤10°C	Cold: >10 & ≤15°C	Mild: >15 & ≤20°C	Warm: >20 & ≤25°C	Very Warm: >25°C
	Belarus	Argentina	Jordan	Angola	Belize
	Chile	Azerbaijan	Lebanon	Bolivia	Brazil
	China	Croatia	Morocco	Colombia	Gabon
	Georgia	Serbia	Peru	Costa Rica	Ghana
	Hungary	Turkey	South Africa	Dominican Republic	Indonesia
	Kazakhstan		Tunisia	Ecuador	Ivory Coast
	Latvia		Uruguay	Egypt	Jamaica
	Lithuania			El Salvador	Malaysia
	Mongolia			Guatemala	Nigeria
	Poland			India	Panama
	Romania			Iraq	Philippines
	Russia			Mexico	Senegal
	Ukraine			Namibia	Venezuela
				Pakistan	
				Vietnam	
				Zambia	
Average 1901-2018 annual temperature	5.863°C	11.938°C	18.087°C	22.657°C	25.986°C

Table 8: Baseline results

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI	(5) ΔEMBI	(6) ΔEMBI
HistoricalTempAnomaly	-0.0614**	-0.0798***	-0.0118			
	(0.0267)	(0.0269)	(0.0507)			
DeviationAdjustedTempAnomaly				-0.219***	-0.233***	-0.235***
				(0.0681)	(0.0633)	(0.0798)
Precipitation		0.197	0.223		0.110	0.0385
		(0.416)	(0.363)		(0.424)	(0.375)
ΔVIX		-0.151***			-0.151***	
		(0.0164)			(0.0164)	
ΔGlobalGovernmentBondIndex		0.0691*			0.0690*	
		(0.0370)			(0.0370)	
ΔUS-TermSpread		-0.102			-0.106	
		(0.199)			(0.199)	
ΔUS-CorporateRiskPremium		-2.445***			-2.443***	
		(0.186)			(0.186)	
ΔUS-10-YearTreasuryYield		-3.689***			-3.684***	
		(0.437)			(0.438)	
Constant	0.740***	0.688***	0.679***	0.777***	0.722***	0.786***
	(0.0239)	(0.0539)	(0.0631)	(0.0284)	(0.0560)	(0.0552)
Observations	10,006	10,006	9,957	10,006	10,006	9,957
R-squared	0.068	0.217	0.524	0.068	0.218	0.524
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	No	Yes	Yes	No
Region×MonthYear FE	No	No	Yes	No	No	Yes

This table shows OLS estimation results of a panel of 54 countries from 1994m1 to 2018m12. ΔEMBI are monthly natural log returns of a country's EMBI index. HistoricalTempAnomaly is the difference between monthly temperature of a country and its 1901-1950 temperature average of the same month. DeviationAdjustedTempAnomaly is the anomaly measure divided by a country's 1901-1950 average of temperature standard deviation. Precipitation is the country-specific average in 1000 mm units. ΔVIX, ΔUS-TermSpread (10-year treasury yield minus 3-month T-Bill yield), ΔUS-CorporateRiskPremium (high corporate bond yield minus investment grade corporate bond yield) and ΔUS-10-YearTreasuryYield are in simple first differences, ΔGlobalGovernmentBondIndex is in natural log differences. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 9: Results for general warmness

	(1) ΔEMBI	(2) ΔEMBI
HistoricalTempAnomaly	0.0596	0.0825
	(0.0834)	(0.117)
VeryColdCountry (percentile) × HistoricalTempAnomaly	-0.0731	
	(0.0802)	
ColdCountry (percentile; base category) × HistoricalTempAnomaly	0	
	(0)	
MildCountry (percentile) × HistoricalTempAnomaly	-0.0639	
	(0.114)	
WarmCountry (percentile) × HistoricalTempAnomaly	-0.224	
	(0.174)	
VeryWarmCountry (percentile) × HistoricalTempAnomaly	-0.491**	
	(0.233)	
VeryColdCountry ($\leq 10°C$) × HistoricalTempAnomaly		-0.0492
		(0.110)
ColdCountry (> 10 & $\leq 15°C$; base category) × HistoricalTempAnomaly		0
		(0)
MildCountry (> 15 & $\leq 20°C$) × HistoricalTempAnomaly		-0.207
		(0.124)
WarmCountry (> 20 & $\leq 25°C$) × HistoricalTempAnomaly		-0.125
		(0.155)
VeryWarmCountry ($> 25°C$) × HistoricalTempAnomaly		-0.547**
		(0.229)
Precipitation	0.0640	0.00819
	(0.406)	(0.393)
Observations	9,957	9,957
R-squared	0.524	0.524
Country FE	Yes	Yes
Region×MonthYear FE	Yes	Yes
Total "very warm" Country Effect	-0.432	-0.464

This table shows OLS estimation results of a panel of 54 countries from 1994m1 to 2018m12. ΔEMBI are monthly natural log returns of a country's EMBI index. HistoricalTempAnomaly is the difference between monthly temperature of a country and its 1901-1950 temperature average of the same month. Each country is grouped into a bin either according to percentiles (see Table 6 for respective countries) or 5°C intervals (see Table 7 for respective countries). One bin is omitted due to multicollinearity (base category). Single terms of the bins are subsumed by time fixed effects. Total "very warm" country effect is the sum of the VeryWarmCountry interaction and the single term of HistoricalTempAnomaly. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 10: Results for seasonality

	(1) ΔEMBI
HistoricalTempAnomaly	0.0511
	(0.102)
VeryLow Temp-StdDev (percentile) × HistoricalTempAnomaly	-0.441**
	(0.199)
Low Temp-StdDev (percentile) × HistoricalTempAnomaly	-0.493*
	(0.281)
Normal Temp-StdDev (percentile; base category) × HistoricalTempAnomaly	0
	(0)
High Temp-StdDev (percentile) × HistoricalTempAnomaly	0.0502
	(0.113)
VeryHigh Temp-StdDev (percentile) × HistoricalTempAnomaly	-0.107
	(0.111)
Precipitation	-0.0100
	(0.396)
Observations	9,957
R-squared	0.525
Country FE	Yes
Region×MonthYear FE	Yes

This table shows OLS estimation results of a panel of 54 countries from 1994m1 to 2018m12. ΔEMBI are monthly natural log returns of a country's EMBI index. HistoricalTempAnomaly is the difference between monthly temperature of a country and its 1901-1950 temperature average of the same month. Each country is grouped into a bin according to percentiles of monthly temperature standard deviation from 1901-2018 (Temp-StdDev). One bin is omitted due to multicollinearity (base category). Single terms of the bins are subsumed by time fixed effects. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 11: Results for month and season effects

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI
HistoricalTempAnomaly	-0.0939	0.0890	-0.00309
	(0.124)	(0.106)	(0.102)
January (adjusted) × HistoricalTempAnomaly	0.0155	-0.167	
	(0.140)	(0.108)	
February (adjusted) × HistoricalTempAnomaly	0.00336	-0.179	
	(0.146)	(0.137)	
March (adjusted) × HistoricalTempAnomaly	0.0532	-0.130	
	(0.190)	(0.136)	
April (adjusted) × HistoricalTempAnomaly	-0.0325	-0.215	
	(0.176)	(0.181)	
May (adjusted; base category in (1)) × HistoricalTempAnomaly	0	-0.183	
	(0)	(0.173)	
June (adjusted) × HistoricalTempAnomaly	0.0704	-0.112	
	(0.273)	(0.220)	
July (adjusted) × HistoricalTempAnomaly	0.347	0.165	
	(0.213)	(0.186)	
August (adjusted) × HistoricalTempAnomaly	0.210	0.0271	
	(0.204)	(0.160)	
September (adjusted) × HistoricalTempAnomaly	0.105	-0.0779	
	(0.243)	(0.238)	
October (adjusted) × HistoricalTempAnomaly	0.309	0.127	
	(0.186)	(0.159)	
November (adjusted) × HistoricalTempAnomaly	-0.0798	-0.263**	
	(0.173)	(0.109)	
December (adjusted; base category in (2)) × HistoricalTempAnomaly	0.183	0	
	(0.173)	(0)	
Spring × HistoricalTempAnomaly			-0.0766
			(0.0935)
Summer × HistoricalTempAnomaly			0.129
			(0.134)
Autumn (base category) × HistoricalTempAnomaly			0
			(0)
Winter × HistoricalTempAnomaly			-0.0175
			(0.0998)
Precipitation	0.362	0.362	0.439
	(0.477)	(0.477)	(0.437)
Observations	9,957	9,957	9,957
R-squared	0.525	0.525	0.524
Single Terms	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes

This table shows OLS estimation results of a panel of 54 countries from 1994m1 to 2018m12. ΔEMBI are monthly natural log returns of a country's EMBI index. HistoricalTempAnomaly is the difference between monthly temperature of a country and its 1901-1950 temperature average of the same month. In columns (1) and (2), months in the southern hemisphere are adjusted to northern hemisphere scaling (January becomes July and so on). One month or season is omitted due to multicollinearity (base category). The single terms of months or seasons are included in the regression but left out in the table to save space. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 12: Results for economic sector specialization: agriculture

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI	(5) ΔEMBI	(6) ΔEMBI
HistoricalTempAnomaly	0.0885		0.0388		0.0627	
	(0.0964)		(0.0781)		(0.0824)	
DeviationAdjustedTempAnomaly		-0.179		-0.290		-0.305*
		(0.251)		(0.191)		(0.153)
AgricultureLandShare	0.0183	0.0164				
	(0.0320)	(0.0316)				
HistoricalTempAnomaly	-0.00219					
× AgricultureLandShare	(0.00144)					
DeviationAdjustedTempAnomaly		-0.00199				
× AgricultureLandShare		(0.00617)				
AgricultureToGDP			0.0188	0.0137		
			(0.0303)	(0.0301)		
HistoricalTempAnomaly			-0.00828			
× AgricultureToGDP			(0.00970)			
DeviationAdjustedTempAnomaly				0.00615		
× AgricultureToGDP				(0.0186)		
AgricultureEmploymentShare					0.0391**	0.0363**
					(0.0167)	(0.0161)
HistoricalTempAnomaly					-0.00364	
× AgricultureEmploymentShare					(0.00323)	
DeviationAdjustedTempAnomaly						0.00317
× AgricultureEmploymentShare						(0.00657)
Precipitation	0.298	0.0889	0.294	0.111	0.211	0.0323
	(0.369)	(0.387)	(0.364)	(0.365)	(0.364)	(0.379)
Observations	8,662	8,662	9,875	9,875	9,957	9,957
R-squared	0.529	0.529	0.528	0.528	0.524	0.524
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes	Yes	Yes	Yes

This table shows OLS estimation results of a panel of 54 countries from 1994m1 to 2018m12. ΔEMBI are monthly natural log returns of a country's EMBI index. HistoricalTempAnomaly is the difference between monthly temperature of a country and its 1901-1950 temperature average of the same month. DeviationAdjustedTempAnomaly is the anomaly measure divided by a country's 1901-1950 average of temperature standard deviation. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 13: Results for economic sector specialization: manufacturing, services and resources

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI	(5) ΔEMBI	(6) ΔEMBI	(7) ΔEMBI	(8) ΔEMBI	(9) ΔEMBI	(10) ΔEMBI
HistoricalTempAnomaly	-0.164		-0.386*		-0.108		-0.203		0.00517	
	(0.104)		(0.228)		(0.205)		(0.214)		(0.0587)	
DeviationAdjustedTempAnomaly		-0.546*		-0.503		0.0826		-4.67e-05		-0.218*
		(0.310)		(0.387)		(0.424)		(0.328)		(0.112)
ManufacutringToGDP	0.0379	0.0339								
	(0.0314)	(0.0330)								
HistoricalTempAnomaly × ManufacutringToGDP	0.00833									
	(0.00709)									
DeviationAdjustedTempAnomaly × ManufacutringToGDP		0.0192								
		(0.0171)								
IndustrialEmploymentShare			-0.0376	-0.0307						
			(0.0290)	(0.0281)						
HistoricalTempAnomaly × IndustrialEmploymentShare			0.0157							
			(0.00955)							
DeviationAdjustedTempAnomaly × IndustrialEmploymentShare				0.0129						
				(0.0174)						
ServicesEmploymentShare					-0.0459*	-0.0427				
					(0.0266)	(0.0259)				
HistoricalTempAnomaly × ServicesEmploymentShare					0.00171					
					(0.00352)					
DeviationAdjustedTempAnomaly × ServicesEmploymentShare						-0.00551				
						(0.00723)				
ServicesToGDP							-0.0410**	-0.0374**		
							(0.0154)	(0.0148)		
HistoricalTempAnomaly × ServicesToGDP							0.00339			
							(0.00392)			
DeviationAdjustedTempAnomaly × ServicesToGDP								-0.00443		
								(0.00614)		
ResourceRentsToGDP									0.0143	0.0111
									(0.0182)	(0.0182)
HistoricalTempAnomaly × ResourceRentsToGDP									-0.00256	
									(0.00218)	
DeviationAdjustedTempAnomaly × ResourceRentsToGDP										-0.00138
										(0.00742)
Precipitation	0.256	0.100	0.174	0.0442	0.222	0.0296	0.296	0.121	0.253	0.0716
	(0.364)	(0.372)	(0.363)	(0.376)	(0.364)	(0.378)	(0.365)	(0.371)	(0.354)	(0.362)
Observations	9,599	9,599	9,957	9,957	9,957	9,957	9,875	9,875	9,273	9,273
R-squared	0.530	0.530	0.524	0.524	0.524	0.524	0.529	0.529	0.531	0.531
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows OLS estimation results of a panel of 54 countries from 1994m1 to 2018m12. ΔEMBI are monthly natural log returns of a country's EMBI index. HistoricalTempAnomaly is the difference between monthly temperature of a country and its 1901-1950 temperature average of the same month. DeviationAdjustedTempAnomaly is the anomaly measure divided by a country's 1901-1950 average of temperature standard deviation. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 14: Results for institutional quality (1): rule of law, control of corruption, civil liberties, political rights

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI	(5) ΔEMBI	(6) ΔEMBI	(7) ΔEMBI	(8) ΔEMBI
HistoricalTempAnomaly	-0.209**		-0.166**		0.137*		0.0984	
	(0.0873)		(0.0816)		(0.0717)		(0.0747)	
DeviationAdjustedTempAnomaly		-0.584***		-0.572***		0.173		-0.0127
		(0.141)		(0.183)		(0.216)		(0.146)
RuleOfLaw	-0.00507	-0.00556						
	(0.00497)	(0.00453)						
HistoricalTempAnomaly × RuleOfLaw	0.00396***							
	(0.00123)							
DeviationAdjustedTempAnomaly × RuleOfLaw		0.00802***						
		(0.00261)						
ControlOfCorruption			-0.00494	-0.00506				
			(0.00497)	(0.00511)				
HistoricalTempAnomaly × ControlOfCorruption			0.00304***					
			(0.00110)					
DeviationAdjustedTempAnomaly × ControlOfCorruption				0.00728**				
				(0.00348)				
CivilLiberties					0.149*	0.177**		
					(0.0771)	(0.0861)		
HistoricalTempAnomaly × CivilLiberties					-0.0454***			
					(0.0152)			
DeviationAdjustedTempAnomaly × CivilLiberties						-0.124**		
						(0.0526)		
PoliticalRights							0.0230	0.0245
							(0.0538)	(0.0551)
HistoricalTempAnomaly × PoliticalRights							-0.0324**	
							(0.0125)	
DeviationAdjustedTempAnomaly × PoliticalRights								-0.0749*
								(0.0397)
Precipitation	0.275	0.114	0.293	0.126	0.218	0.00310	0.231	0.0241
	(0.374)	(0.387)	(0.374)	(0.388)	(0.371)	(0.383)	(0.368)	(0.374)
Observations	9,688	9,688	9,688	9,688	9,929	9,929	9,940	9,940
R-squared	0.502	0.502	0.502	0.502	0.524	0.525	0.524	0.524
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows OLS estimation results of a panel of 54 countries from 1994m1 to 2018m12. ΔEMBI are monthly natural log returns of a country's EMBI index. HistoricalTempAnomaly is the difference between monthly temperature of a country and its 1901-1950 temperature average of the same month. DeviationAdjustedTempAnomaly is the anomaly measure divided by a country's 1901-1950 average of temperature standard deviation. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 15: Results for institutional quality (2): income redistribution, polity2, democratic governments, authoritarian governments

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI	(5) ΔEMBI	(6) ΔEMBI	(7) ΔEMBI	(8) ΔEMBI
HistoricalTempAnomaly	-0.0798		-0.0525		-0.118**		0.0503	
	(0.0595)		(0.0453)		(0.0530)		(0.0548)	
DeviationAdjustedTempAnomaly		-0.292***		-0.373***		-0.532***		-0.144**
		(0.0880)		(0.117)		(0.164)		(0.0617)
IncomeRedistribution	0.0209	0.0150						
	(0.0945)	(0.0965)						
HistoricalTempAnomaly × IncomeRedistribution	0.00499***							
	(0.00152)							
DeviationAdjustedTempAnomaly × IncomeRedistribution		0.0163						
		(0.0138)						
Polity2			-0.0120	-0.0171				
			(0.0167)	(0.0199)				
HistoricalTempAnomaly × Polity2			0.0115**					
			(0.00448)					
DeviationAdjustedTempAnomaly × Polity2				0.0301**				
				(0.0142)				
DemocraticGovernments					-0.0274	-0.0364		
					(0.0285)	(0.0320)		
HistoricalTempAnomaly × DemocraticGovernments					0.0196**			
					(0.00736)			
DeviationAdjustedTempAnomaly × DemocraticGovernments						0.0521**		
						(0.0217)		
AuthoritarianGovernments							0.0449	0.0596
							(0.0373)	(0.0481)
HistoricalTempAnomaly × AuthoritarianGovernments							-0.0292***	
							(0.0101)	
DeviationAdjustedTempAnomaly × AuthoritarianGovernments								-0.0775**
								(0.0321)
Precipitation	0.446	0.333	0.322	0.140	0.315	0.133	0.336	0.154
	(0.411)	(0.421)	(0.383)	(0.382)	(0.392)	(0.389)	(0.389)	(0.386)
Observations	8,308	8,308	9,655	9,655	9,517	9,517	9,517	9,517
R-squared	0.539	0.539	0.542	0.542	0.548	0.548	0.548	0.548
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows OLS estimation results of a panel of 54 countries from 1994m1 to 2018m12. ΔEMBI are monthly natural log returns of a country's EMBI index. HistoricalTempAnomaly is the difference between monthly temperature of a country and its 1901-1950 temperature average of the same month. DeviationAdjustedTempAnomaly is the anomaly measure divided by a country's 1901-1950 average of temperature standard deviation. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 16: Results for climate-related institutional quality

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI	(5) ΔEMBI	(6) ΔEMBI
HistoricalTempAnomaly	-0.721**		-0.484***		0.0386	
	(0.346)		(0.168)		(0.343)	
DeviationAdjustedTempAnomaly		-1.264*		-0.957***		-1.040
		(0.697)		(0.275)		(0.757)
ND-GAIN	-0.0500	-0.0461				
	(0.0357)	(0.0333)				
HistoricalTempAnomaly	0.0132**					
× ND-GAIN	(0.00631)					
DeviationAdjustedTempAnomaly		0.0211				
× ND-GAIN		(0.0138)				
ReadinessIndex			-2.293	-2.225		
			(1.597)	(1.463)		
HistoricalTempAnomaly			1.052***			
× ReadinessIndex			(0.331)			
DeviationAdjustedTempAnomaly				1.908***		
× ReadinessIndex				(0.680)		
VulnerabilityIndex					19.93	20.43
					(13.81)	(13.42)
HistoricalTempAnomaly					-0.186	
× VulnerabilityIndex					(0.889)	
DeviationAdjustedTempAnomaly						1.816
× VulnerabilityIndex						(1.802)
Precipitation	0.336	0.224	0.332	0.213	0.400	0.178
	(0.365)	(0.379)	(0.362)	(0.385)	(0.356)	(0.365)
Observations	9,194	9,194	9,194	9,194	9,194	9,194
R-squared	0.509	0.510	0.510	0.510	0.509	0.510
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes	Yes	Yes	Yes

This table shows OLS estimation results of a panel of 54 countries from 1994m1 to 2018m12. ΔEMBI are monthly natural log returns of a country's EMBI index. HistoricalTempAnomaly is the difference between monthly temperature of a country and its 1901-1950 temperature average of the same month. DeviationAdjustedTempAnomaly is the anomaly measure divided by a country's 1901-1950 average of temperature standard deviation. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 17: Results for combining relevant channels

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI
HistoricalTempAnomaly	-0.145*	-0.233***	-0.151*	-0.137
	(0.0764)	(0.0845)	(0.0893)	(0.137)
GDPPerCapita	-5.83e-05	-4.19e-05	-4.04e-05	-3.57e-05
	(4.14e-05)	(4.06e-05)	(4.03e-05)	(3.98e-05)
HistoricalTempAnomaly	1.70e-05**	7.21e-06	5.97e-06	2.71e-06
× GDPPerCapita	(6.54e-06)	(7.80e-06)	(7.54e-06)	(6.80e-06)
RuleOfLaw		-0.00315	-0.00235	-0.00414
		(0.00477)	(0.00474)	(0.00467)
HistoricalTempAnomaly × RuleOfLaw		0.00326**	0.00317**	0.00381***
		(0.00149)	(0.00138)	(0.00133)
DeviationAdjustedTempAnomaly			-0.314***	
			(0.107)	
VeryColdCountry ($\leq$ 10°C)				-0.0508
× HistoricalTempAnomaly				(0.101)
ColdCountry ($>$ 10 & $\leq$ 15°C; base category)				0
× HistoricalTempAnomaly				(0)
MildCountry ($>$ 15 & $\leq$ 20°C)c				-0.217
× HistoricalTempAnomaly				(0.131)
WarmCountry ($>$ 20 & $\leq$ 25°C)				-0.0422
× HistoricalTempAnomaly				(0.158)
VeryWarmCountry ($>$ 25°C)				-0.539**
× HistoricalTempAnomaly				(0.237)
Precipitation	0.194	0.267	0.0751	0.0683
	(0.367)	(0.375)	(0.387)	(0.392)
Observations	9,957	9,688	9,688	9,688
R-squared	0.524	0.502	0.502	0.502
Country FE	Yes	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes	Yes

This table shows OLS estimation results of a panel of 54 countries from 1994m1 to 2018m12. ΔEMBI are monthly natural log returns of a country's EMBI index. HistoricalTempAnomaly is the difference between monthly temperature of a country and its 1901-1950 temperature average of the same month. DeviationAdjustedTempAnomaly is the anomaly measure divided by a country's 1901-1950 average of temperature standard deviation. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 18: Robustness tests: changing fixed effects specification

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI	(5) ΔEMBI	(6) ΔEMBI	(7) ΔEMBI	(8) ΔEMBI	(9) ΔEMBI
HistoricalTempAnomaly		0.0125	-0.222**		0.0599	-0.194**		0.0913	-0.241***
		(0.0795)	(0.0830)		(0.112)	(0.0952)		(0.113)	(0.0852)
DeviationAdjustedTempAnomaly	-0.237***			-0.179*			-0.238***		
	(0.0743)			(0.106)			(0.0880)		
VeryColdCountry × HistoricalTempAnomaly		-0.0482			-0.0355			-0.0470	
		(0.0918)			(0.104)			(0.110)	
ColdCountry (base category) × HistoricalTempAnomaly		0			0			0	
		(0)			(0)			(0)	
MildCountry × HistoricalTempAnomaly		-0.120			-0.176			-0.234*	
		(0.0994)			(0.118)			(0.117)	
WarmCountry × HistoricalTempAnomaly		-0.0984			-0.114			-0.196	
		(0.118)			(0.146)			(0.156)	
VeryWarmCountry × HistoricalTempAnomaly		-0.428**			-0.380**			-0.562**	
		(0.165)			(0.185)			(0.249)	
RuleOfLaw			-0.00366						-0.00562
			(0.00499)						(0.00500)
HistoricalTempAnomaly × RuleOfLaw			0.00346**			0.00358***			0.00457***
			(0.00148)			(0.00126)			(0.00117)
Precipitation	-0.0832	-0.104	0.286	0.0590	0.0555	0.234	0.481	0.428	0.776
	(0.440)	(0.443)	(0.411)	(0.408)	(0.404)	(0.380)	(0.672)	(0.690)	(0.668)
Observations	10,006	10,006	9,699	9,951	9,951	9,682	9,957	9,957	9,688
R-squared	0.418	0.418	0.395	0.571	0.572	0.552	0.532	0.532	0.510
Country FE	Yes	Yes	Yes	No	No	No	No	No	No
MonthYear FE	Yes	Yes	Yes	No	No	No	No	No	No
Region×MonthYear FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year FE	No	No	No	Yes	Yes	Yes	No	No	No
Country×Quarter FE	No	No	No	No	No	No	Yes	Yes	Yes
Total "very warm" Country Effect		-0.415			-0.320			-0.471	

This table shows robustness checks for the deviation-adjusted temperature variable (Table 8, column (6)), the bin-regression analyzing the warmness of countries using 5°C-intervals (Table 9, column (2)) and the interaction with institutional characteristics (rule of law index, Table 14, column (1)). The total "very warm" country effect is derived by adding the coefficients of the "very warm" interaction effect and the single term of HistoricalTempAnomaly. I change fixed effects as described in the table. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 19: Robustness tests: changing dependent variable

	(1) ΔEMBI Spread	(2) ΔEMBI Spread	(3) ΔEMBI Spread	(4) ΔCDS Spread	(5) ΔCDS Spread
DeviationAdjustedTempAnomaly	3.667*			8.276	
	(1.837)			(5.990)	
HistoricalTempAnomaly		-1.649	4.776**		11.17**
		(2.248)	(2.287)		(4.513)
VeryColdCountry × HistoricalTempAnomaly		1.354			
		(2.182)			
ColdCountry (base category) × HistoricalTempAnomaly		0			
		(0)			
MildCountry × HistoricalTempAnomaly		3.301			
		(2.208)			
WarmCountry × HistoricalTempAnomaly		1.766			
		(2.580)			
VeryWarmCountry × HistoricalTempAnomaly		11.27*			
		(5.734)			
RuleOfLaw			-0.0610		-0.0811
			(0.146)		(0.217)
HistoricalTempAnomaly × RuleOfLaw			-0.0940***		-0.187**
			(0.0350)		(0.0744)
Precipitation	-14.57*	-13.10	-15.86*	19.17	15.03
	(8.247)	(8.715)	(8.030)	(18.99)	(15.71)
Observations	9,610	9,610	9,491	4,277	4,277
R-squared	0.463	0.464	0.456	0.349	0.351
Number of Countries	54	54	54	37	37
Country FE	Yes	Yes	Yes	Yes	Yes
Region× MonthYear FE	Yes	Yes	Yes	Yes	Yes

This table shows robustness checks for the deviation-adjusted temperature variable (Table 8, column (6)), the bin-regression analyzing the warmness of countries using 5°C-intervals (Table 9, column (2)) and the interaction with institutional characteristics (rule of law index, Table 14, column (1)). Columns (1)-(3) use the first difference of the EMBI spread, and columns (4)-(5) the first difference of the CDS spread as a new dependent variable. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 20: Robustness tests: introducing lag structure

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI
DeviationAdjustedTempAnomaly	-0.275**		
	(0.125)		
HistoricalTempAnomaly		0.0474	-0.204**
		(0.109)	(0.0935)
VeryWarmTemp5BinDisc × HistoricalTempAnomaly		-0.569*	
		(0.297)	
RuleOfLaw			-0.00739
			(0.00642)
HistoricalTempAnomaly × RuleOfLaw			0.00369**
			(0.00139)
Precipitation	0.364	0.291	0.282
	(0.404)	(0.396)	(0.391)
L1.DeviationAdjustedTempAnomaly	0.0914		
	(0.0926)		
L2.DeviationAdjustedTempAnomaly	0.0172		
	(0.144)		
L3.DeviationAdjustedTempAnomaly	0.0130		
	(0.143)		
L4.DeviationAdjustedTempAnomaly	-0.0805		
	(0.156)		
L5.DeviationAdjustedTempAnomaly	0.00625		
	(0.0976)		
L6.DeviationAdjustedTempAnomaly	-0.172*		
	(0.103)		
L7.DeviationAdjustedTempAnomaly	-0.121		
	(0.0946)		
L8.DeviationAdjustedTempAnomaly	0.0379		
	(0.120)		
L9.DeviationAdjustedTempAnomaly	0.0750		
	(0.0779)		
L10.DeviationAdjustedTempAnomaly	-0.0195		
	(0.134)		
L11.DeviationAdjustedTempAnomaly	-0.0749		
	(0.0991)		
L12.DeviationAdjustedTempAnomaly	0.177		
	(0.125)		
L1.HistoricalTempAnomaly × RuleOfLaw			0.00118
			(0.00144)
L2.HistoricalTempAnomaly × RuleOfLaw			-0.00171
			(0.00144)
L3.HistoricalTempAnomaly × RuleOfLaw			-0.00102
			(0.00130)
L4.HistoricalTempAnomaly × RuleOfLaw			0.000323
			(0.00108)
L5.HistoricalTempAnomaly × RuleOfLaw			-0.000594
			(0.00195)
L6.HistoricalTempAnomaly × RuleOfLaw			0.00290*
			(0.00153)
L7.HistoricalTempAnomaly × RuleOfLaw			-0.00241
			(0.00174)
L8.HistoricalTempAnomaly × RuleOfLaw			0.00219
			(0.00158)
L9.HistoricalTempAnomaly × RuleOfLaw			0.00121
			(0.00151)
L10.HistoricalTempAnomaly × RuleOfLaw			0.000187
			(0.00134)
L11.HistoricalTempAnomaly × RuleOfLaw			6.45e-05
			(0.00207)
L12.HistoricalTempAnomaly × RuleOfLaw			0.00113
			(0.00147)
Observations	9,842	9,842	9,688
R-squared	0.511	0.514	0.503
Country FE	Yes	Yes	Yes
Region× MonthYear FE	Yes	Yes	Yes
Lag and Single Terms		Yes	Yes

This table shows robustness checks for the deviation-adjusted temperature variable (Table 8, column (6)), the bin-regression analyzing the warmness of countries using 5°C-intervals (Table 9, column (2)) and the interaction with institutional characteristics (rule of law index, Table 14, column (1)). Estimation for column (2) includes all other bin-category interactions ("cold" country as base category). Estimations for columns (2) and (3) also include all lagged single terms and interactions of HistoricalTempAnomaly. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 21: Robustness tests: changing historical average period (1930, 1940)

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI	(5) ΔEMBI	(6) ΔEMBI
DeviationAdjustedTempAnomaly (1930)	-0.213***					
	(0.0720)					
HistoricalTempAnomaly (1930)		0.0789	-0.196**			
		(0.113)	(0.0837)			
VeryColdCountry		-0.0444				
× HistoricalTempAnomaly (1930)		(0.107)				
ColdCountry (base category)		0				
× HistoricalTempAnomaly (1930)		(0)				
MildCountry		-0.193				
× HistoricalTempAnomaly (1930)		(0.122)				
WarmCountry		-0.112				
× HistoricalTempAnomaly (1930)		(0.152)				
VeryWarmCountry		-0.531**				
× HistoricalTempAnomaly (1930)		(0.224)				
RuleOfLaw			-0.00521			-0.00518
			(0.00488)			(0.00493)
HistoricalTempAnomaly (1930)			0.00376***			
× RuleOfLaw			(0.00113)			
DeviationAdjustedTempAnomaly (1940)				-0.218***		
				(0.0743)		
HistoricalTempAnomaly (1940)					0.0835	-0.201**
					(0.116)	(0.0850)
VeryColdCountry					-0.0453	
× HistoricalTempAnomaly (1940)					(0.109)	
ColdCountry (base category)					0	
× HistoricalTempAnomaly (1940)					(0)	
MildCountry					-0.199	
× HistoricalTempAnomaly (1940)					(0.122)	
WarmCountry					-0.113	
× HistoricalTempAnomaly (1940)					(0.155)	
VeryWarmCountry					-0.537**	
× HistoricalTempAnomaly (1940)					(0.225)	
HistoricalTempAnomaly (1940)						0.00392***
× RuleOfLaw						(0.00118)
Precipitation	0.0281	-0.0191	0.267	0.0423	0.0147	0.276
	(0.380)	(0.403)	(0.375)	(0.377)	(0.395)	(0.374)
Observations	9,957	9,957	9,688	9,957	9,957	9,688
R-squared	0.524	0.524	0.502	0.524	0.524	0.502
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Total "very warm" Country Effect		-0.452			-0.453	

This table shows robustness checks for the deviation-adjusted temperature variable (Table 8, column (6)), the bin-regression analyzing the warmness of countries using 5°C-intervals (Table 9, column (2)) and the interaction with institutional characteristics (rule of law index, Table 14, column (1)). Historical temperature averages are calculated from 1901 to 1930 or 1940 instead of 1950, as shown in the table. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 22: Robustness tests: changing historical average period (1960, 1970)

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI	(5) ΔEMBI	(6) ΔEMBI
DeviationAdjustedTempAnomaly (1960)	-0.244***					
	(0.0825)					
HistoricalTempAnomaly (1960)		0.0801	-0.215**			
		(0.116)	(0.0877)			
VeryColdCountry		-0.0517				
× HistoricalTempAnomaly (1960)		(0.109)				
ColdCountry (base category)		0				
× HistoricalTempAnomaly (1960)		(0)				
MildCountry		-0.211*				
× HistoricalTempAnomaly (1960)		(0.123)				
WarmCountry		-0.128				
× HistoricalTempAnomaly (1960)		(0.156)				
VeryWarmCountry		-0.541**				
× HistoricalTempAnomaly (1960)		(0.229)				
RuleOfLaw			-0.00505			-0.00503
			(0.00498)			(0.00498)
HistoricalTempAnomaly (1960)			0.00401***			
× RuleOfLaw			(0.00123)			
DeviationAdjustedTempAnomaly (1970)				-0.253***		
				(0.0864)		
HistoricalTempAnomaly (1970)					0.0757	-0.219**
					(0.116)	(0.0878)
VeryColdCountry					-0.0470	
× HistoricalTempAnomaly (1970)					(0.109)	
ColdCountry (base category)					0	
× HistoricalTempAnomaly (1970)					(0)	
MildCountry					-0.214*	
× HistoricalTempAnomaly (1970)					(0.123)	
WarmCountry					-0.122	
× HistoricalTempAnomaly (1970)					(0.155)	
VeryWarmCountry					-0.553**	
× HistoricalTempAnomaly (1970)					(0.233)	
HistoricalTempAnomaly (1970)						0.00405***
× RuleOfLaw						(0.00124)
Precipitation	0.0384	0.0154	0.272	0.0467	0.0178	0.272
	(0.375)	(0.390)	(0.374)	(0.376)	(0.389)	(0.373)
Observations	9,957	9,957	9,688	9,957	9,957	9,688
R-squared	0.524	0.524	0.502	0.524	0.524	0.502
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Total "very warm" Country Effect		-0.461			-0.477	

This table shows robustness checks for the deviation-adjusted temperature variable (Table 8, column (6)), the bin-regression analyzing the warmness of countries using 5°C-intervals (Table 9, column (2)) and the interaction with institutional characteristics (rule of law index, Table 14, column (1)). Historical temperature averages are calculated from 1901 to 1960 or 1970 instead of 1950, as shown in the table. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 23: Robustness tests: dropping countries with lower data coverage and larger landmass

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI	(5) ΔEMBI	(6) ΔEMBI
DeviationAdjustedTempAnomaly	-0.239***			-0.315***		
	(0.0861)			(0.108)		
HistoricalTempAnomaly		0.0994	-0.184*		-0.0587	-0.336***
		(0.131)	(0.0993)		(0.0699)	(0.0875)
VeryColdCountry		-0.0286			0.0559	
× HistoricalTempAnomaly		(0.120)			(0.0898)	
ColdCountry (base category)		0			0	
× HistoricalTempAnomaly		(0)			(0)	
MildCountry		-0.231*			-0.0797	
× HistoricalTempAnomaly		(0.137)			(0.0784)	
WarmCountry		-0.104			-0.0143	
× HistoricalTempAnomaly		(0.166)			(0.120)	
VeryWarmCountry		-0.642***			-0.384	
× HistoricalTempAnomaly		(0.248)			(0.239)	
RuleOfLaw			-0.00479			-0.00261
			(0.00501)			(0.00513)
HistoricalTempAnomaly			0.00381***			0.00514***
× RuleOfLaw			(0.00140)			(0.00138)
Precipitation	0.0319	-0.0355	0.322	-0.0579	-0.0419	0.0934
	(0.418)	(0.445)	(0.414)	(0.522)	(0.539)	(0.523)
Observations	8,746	8,746	8,477	7,641	7,641	7,550
R-squared	0.529	0.529	0.505	0.524	0.524	0.509
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Countries	39	39	39	44	44	44
Total "very warm" Country Effect		-0.543			-0.443	

This table shows robustness checks for the deviation-adjusted temperature variable (Table 8, column (6)), the bin-regression analyzing the warmness of countries using 5°C-intervals (Table 9, column (2)) and the interaction with institutional characteristics (rule of law index, Table 14, column (1)). In columns (1)-(3), all countries with ΔEMBI data of fewer than ten years are dropped. In columns (4)-(6), the ten countries with the largest landmass are dropped. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 24: Robustness tests: other temperature anomaly measures

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI
HistoricalDeviationAnomaly	-0.271**	-0.256*	-0.445***
	(0.121)	(0.152)	(0.155)
VeryColdCountry		-0.0280	
× HistoricalDeviationAnomaly		(0.179)	
ColdCountry (base category)		0	
× HistoricalDeviationAnomaly		(0)	
MildCountry		0.197	
× HistoricalDeviationAnomaly		(0.259)	
WarmCountry		-0.0638	
× HistoricalDeviationAnomaly		(0.385)	
VeryWarmCountry		-0.419	
× HistoricalDeviationAnomaly		(0.439)	
RuleOfLaw			-0.00175
			(0.00544)
HistoricalDeviationAnomaly			0.00395
× RuleOfLaw			(0.00356)
Precipitation	0.209	0.214	0.310
	(0.361)	(0.358)	(0.363)
Observations	9,957	9,957	9,688
R-squared	0.524	0.524	0.502
Country FE	Yes	Yes	Yes
Region×MonthYear FE	Yes	Yes	Yes

This table shows robustness checks for the deviation-adjusted temperature variable (Table 8, column (6)), the bin-regression analyzing the warmness of countries using 5°C-intervals (Table 9, column (2)) and the interaction with institutional characteristics (rule of law index, Table 14, column (1)). HistoricalDeviationAnomaly is a country's standard deviation of temperature over the (rolling) past 12 months minus its 1901-1950 standard deviation of temperature. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

Table 25: Robustness tests: Paris Agreement as transition shock

	(1) ΔEMBI	(2) ΔEMBI	(3) ΔEMBI	(4) ΔEMBI
HistoricalTempAnomaly	-0.00387		0.0963	-0.211**
	(0.0608)		(0.147)	(0.104)
HistoricalTempAnomaly × PostParis	-0.0363		-0.0631	0.0255
	(0.0651)		(0.159)	(0.129)
DeviationAdjustedTempAnomaly		-0.246***		
		(0.0873)		
DeviationAdjustedTempAnomaly × PostParis		0.0522		
		(0.0843)		
HistoricalTempAnomaly × VeryWarmCountry			-0.608**	
			(0.257)	
VeryWarmCountry × PostParis			-0.335	
			(0.430)	
HistoricalTempAnomaly × VeryWarmCountry × PostParis			0.375	
			(0.340)	
RuleOfLaw				-0.00551
				(0.00504)
HistoricalTempAnomaly × RuleOfLaw				0.00415***
				(0.00146)
RuleOfLaw × PostParis				0.00255
				(0.00374)
HistoricalTempAnomaly × RuleOfLaw × PostParis				-0.00113
				(0.00207)
Precipitation	0.224	0.0364	0.0261	0.274
	(0.363)	(0.376)	(0.398)	(0.374)
Observations	9,957	9,957	9,957	9,688
R-squared	0.524	0.524	0.525	0.502
Country FE	Yes	Yes	Yes	Yes
Region× MonthYear FE	Yes	Yes	Yes	Yes
Other Bin Terms			Yes	

This table shows robustness checks for the temperature anomaly measure (Table 8, column (3)), the deviation-adjusted temperature variable (Table 8, column (6)), the bin-regression analyzing the warmness of countries using 5°C-intervals (Table 9, column (2)) and the interaction with institutional characteristics (rule of law index, Table 14, column (1)). PostParis is a dummy with value 1 after the Paris Climate Agreement in December 2015. Estimation in column (3) also includes all other bin categories (cold as base category) and respective interactions. Standard errors (in parentheses) are clustered at the country level, ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. See Table 26 for variable definitions and sources.

10 Appendix

Table 26: Description and sources of variables

Variable	Description	Source
Variables in Baseline Regression (Section 4)		
ΔEMBI	Monthly change in natural logarithm of Emerging Market Bond Index (Global) (winsorized at 1st and 99th percentile)	J.P. Morgan
Historical Temperature Anomaly (HistoricalTempAnomaly)	Difference between monthly temperature of a country and its 1901-1950 temperature average of the same month	Climatic Research Unit, see Harris et al. (2020)
Deviation-Adjusted Temperature Anomaly (DeviationAdjusted-TempAnomaly)	HistoricalTempAnomaly divided by a country's 1901-1950 standard deviation of monthly temperature	Climatic Research Unit, see Harris et al. (2020)
Precipitation	Precipitation in units of 1000 mm per month	Climatic Research Unit, see Harris et al. (2020)
ΔVIX	Monthly first difference in VIX volatility index (winsorized at 1st and 99th percentile)	CBOE
ΔUS-CorporateRiskPremium	Monthly first difference in spread between the S&P US high yield corporate bond index and the corresponding investment grade index (winsorized at 1st and 99th percentile)	S&P
ΔUS-10-YearTreasuryYield	Monthly first difference in the yield of the 10-year US Treasury bond (winsorized at 1st and 99th percentile)	Datastream
ΔUS-TermSpread	Monthly first difference in spread between 10-year US Treasury yield and 3-month US T-Bill yield (winsorized at 1st and 99th percentile)	Datastream, Federal Reserve
ΔGlobalGovernment BondIndex	Monthly change in natural logarithm of Bank Of America Merrill Lynch Global Government Index (winsorized at 1st and 99th percentile)	Merrill Lynch
Variables in Interaction and Bin Regressions (Section 5)		
Very cold, cold, mild, warm, very warm country (percentile)	Countries are grouped into a bin according to percentile distribution of average annual temperature (1901-2018), 1st-20th (very cold), 21st-40th (cold) percentile and so on	
Very cold, cold, mild, warm, very warm country (5°C- interval)	Countries are grouped into a bin according to 5°C- intervals ≤ 10°C (very cold), > 10 & ≤ 15°C (cold), > 15 & ≤ 20°C (mild), > 20 & ≤ 25°C (warm), > 25°C (very warm)	
Very low, low, normal, high, very high temperature standard deviation (Temp-StdDev)	Countries are grouped into a bin according to percentile distribution of monthly temperature standard deviation (1901-2018), 1st-20th (very low), 21st-40th (low) percentile and so on	
Spring	Dummy, 1 in months March-May for northern and September-November for southern hemisphere countries	
Summer	Dummy, 1 in months June-August for northern and December-February for southern hemisphere countries	
Autumn	Dummy, 1 in months September-November for northern and March-May for southern hemisphere countries	
Winter	Dummy, 1 in months December-February for northern and June-August for southern hemisphere countries	
Agriculture Land Share	Agricultural land (% of total land area)	World Bank
Agriculture to GDP	Value added of agriculture (% of gross domestic product)	World Bank
Agriculture Employment Share	Employment in agriculture (% of total employment)	World Bank
Manufacturing to GDP	Value added of manufacturing (% of gross domestic product)	World Bank
Industrial Employment Share	Employment in industry (% of total employment)	World Bank
Services Employment Share	Employment in services (% of total employment)	World Bank

Table 26: Description and sources of variables

Services to GDP	Value added of services (% of gross domestic product)	World Bank
Rule of Law	Rule of law rank (the extend of which agents have confidence in and abide by the rules of society; linearly interpolated)	World Bank
Control of Corruption	Control of corruption rank (the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests; linearly interpolated)	World Bank
Civil Liberties	Countries and territories with a rating of 1 enjoy a wide range of civil liberties. Countries and territories with a rating of 7 have few or no civil liberties	Freedom House
Political Rights	Countries and territories with a rating of 1 enjoy a wide range of political rights, including free and fair elections. Countries and territories with a rating of 7 have few or no political rights	Freedom House
Income Redistribution	Absolute income redistribution (market income inequality minus net-income inequality)	Solt (2019)
Polity2	Unified polity scale that ranges from +10 (strongly democratic) to -10 (strongly autocratic)	Center for Systemic Peace
Democratic Government	Scale that ranges from 0 (not democratic) to +10 (strongly democratic) government	Center for Systemic Peace
Authoritarian Government	Scale that ranges from 0 (not authoritarian) to +10 (strongly authoritarian) government	Center for Systemic Peace
ND-GAIN	Notre Dame Global Adaption Index; ND-GAIN brings together over 74 variables to form 45 core indicators to measure vulnerability and readiness to climate change	Notre Dame Global Adaption Initiative
Readiness Index	Readiness component of ND-GAIN; measures readiness by considering a country's ability to leverage investments to climate adaptation actions	Notre Dame Global Adaption Initiative
Vulnerability Index	Vulnerability component of ND-GAIN; measures propensity or predisposition of human societies to be negatively impacted by climate hazards	Notre Dame Global Adaption Initiative
GDP per Capita	Gross domestic product per capita in constant 2010-US-dollar prices	World Bank
Variables in Robustness Tests (Section 6)		
ΔEMBI Spread	Monthly first difference in Emerging Market Bond Spread (Global) (winsorized at 1st and 99th percentile)	J.P. Morgan
ΔCDS Spread	Monthly first difference in sovereign CDS Spread (winsorized at 1st and 99th percentile)	Thomson Reuters CDS
Historical Deviation Anomaly (HistoricalDeviationAnomaly)	Difference between 12-month rolling temperature standard deviation of a country and its 1901-1950 standard deviation of temperature	Climatic Research Unit, see Harris et al. (2020)
Post Paris	Dummy that is 1 after Paris Agreement (December 2015)	
Further data used		
Natural Disasters	Date of drought, earthquake, epidemic, heat wave, flood, impact, insect infestation, landslide, mass movement, storm, volcanic activity, wildfire (total deaths, damage and affected people for certain disasters)	International Disaster Database
Stock Returns	Natural log returns of stock market index	MSCI, S&P
Accumulated CO_2 Emissions	Accumulated CO_2 emissions of every country and the world since 1751	Global Carbon Project, retrieved via ourworldindata.org
Population	Total population of every country and the world in 2017	World Bank

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