Heat Distributed Unequally in the Sovereign Bond Market

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Abstract

We study how heat shocks are priced in sovereign bond markets. Heat shocks differ from the disaster risks studied in prior work: their expected output losses are small, but their variance is large. We show that this distinction is economically meaningful. Incorporating heat shocks in a quantitative sovereign default model calibrated to the Dominican Republic, we find that low mean losses paired with high uncertainty are sufficient to widen spreads, raise default probabilities, and reduce equilibrium debt, as forward-looking lenders demand compensation for the added risk. We test these predictions in a panel of 76 countries over 1995–2017. Heat shocks widen bond and CDS spreads and lower debt-to-GDP, but the effect is concentrated among emerging markets, whose heat exposure is fat-tailed and whose larger agricultural sectors amplify transmission. Climate risk thus operates through an uncertainty channel and falls on economies least responsible for it.

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Contents

1 Introduction 2

2 Literature Review 5

3 Data and Descriptive Statistics 7

4 Sovereign Debt Model 13
- 4.1 General set-up . . . 13
  - 4.1.1 The government . . . 13
  - 4.1.2 The financial market . . . 13
  - 4.1.3 The solving algorithm . . . 14
  - 4.1.4 How heat shocks impact market outcomes . . . 15
  - 4.1.5 Heat shocks versus hurricane shocks . . . 16
- 4.2 The optimization problem . . . 18
  - 4.2.1 The government . . . 18
  - 4.2.2 The financial market . . . 20

5 Parameterization 20

6 Quantitative Analysis 22
- 6.1 Default probabilities . . . 23
- 6.2 The impact of uncertainty . . . 24

7 Empirical Analysis 25
- 7.1 Empirical specification . . . 25
  - 7.1.1 Heat shocks direct and indirect effects . . . 26
  - 7.1.2 Debt, GDP growth and default risks . . . 28
- 7.2 Heterogeneity . . . 30
  - 7.2.1 Linking agriculture to heat shocks . . . 32

8 Conclusion 34

9 Appendix 39

1 Introduction

Climate change is an uphill battle for sovereigns. Global average surface temperatures have already increased by 1.1°C in 2020 compared to the pre-industrial average (1850–1900) and are projected to increase by 2.7°C by 2100 IPCC (2023) under the baseline scenario. Global warming is associated with more frequent and severe temperature anomalies as illustrated in Figure 1 and 2, and hence the frequency and intensity of heat shocks are expected to increase across the world. This carries implications for sovereigns when they issue debt, as they will possibly face tighter financial market conditions when bond markets try to price in states of the world with more severe heat shocks.

The focus of our paper is to analyze the macroeconomic and financial effects of heat shocks, defined as deviations in the frequency and intensity of heatwaves relative to their historical averages. Heat shocks are low mean, high uncertainty events in terms of damages compared to e.g. other climate disasters such as floods or hurricanes (Weitzman, 2011; Callahan and Mankin, 2022). The case for studying heat shocks over other climate shocks is interesting from the following viewpoints. First, heat shocks affect a broad cross-section of countries globally, making them a particularly relevant object of study for sovereign debt markets. Second, among all extreme events associated with climate change, including floods, sea-level rise, and hurricanes, heat is expected to rank among the most damaging conditional on the tail events materializing. Estimates by Hsiang et al. (2017) indicate that heat related economic damages may amount to several percentage points of GDP by the end of the century, driven by higher energy expenditures, excess mortality, and reduced labor productivity. By contrast, estimates by Hallegatte et al. (2013) suggest that economic damages from sea-level rise are expected to amount to only 0.1% of GDP. In addition, insurance policies against heat risk are nearly non-existent, whereas private and public insurance policies are available for flood or hurricane risk, leaving sovereigns exposed to larger losses (Goering, 2020).

A key contribution of this paper is to contrast two types of disaster risk. Prior work by Mallucci (2022) has emphasized disasters with high mean losses and relatively low uncertainty. In contrast, heat shocks exhibit low mean losses but high uncertainty: the direct losses on GDP are modest, but the distribution of the disaster is characterized by high variance, i.e. rare but extreme realizations. Our paper argues that this distinction matters. Even when expected damages are small, high uncertainty coupled with forward-looking agents can lead to adverse effects for the sovereign.

To formalize this mechanism, we integrate heat shocks into the quantitative sovereign default model of Mallucci (2022). We reinterpret the disaster risk parameter in the income process as a heat shock parameter and analyze the effects of uncertainty on macroeconomic and financial outcomes using a heat shock parameter with a low mean impact and high standard deviation. The adverse effects of uncertainty are captured through forward-looking agents in the financial market, where sovereigns want to self-insure against higher uncertainty in future income streams. In equilibrium, the financial markets react by imposing a risk premium on the higher uncertainty inflicted by heat shocks.

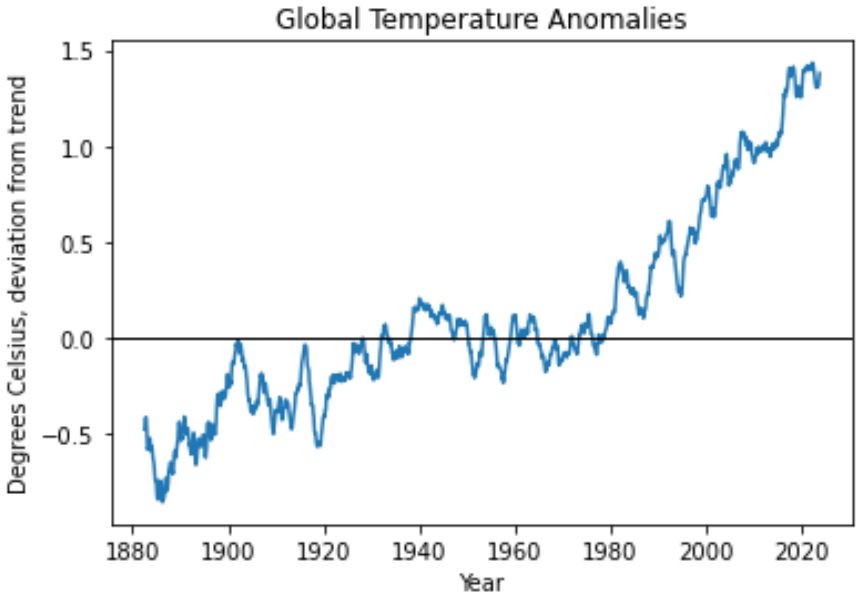


Figure 1: Long-run time series of global temperature anomalies, defined as deviations from trend (1955–1965). Source: University of East Anglia Climatic Research Unit

We calibrate the model to an emerging market with access to deep liquid international sovereign bond markets, i.e. the Dominican Republic, and compare results with Mallucci (2022), who employs a high mean and low uncertainty disaster risk parameter. The model is calibrated to assess how historical heat shocks affect the borrowing decisions of a small open economy such as the Dominican Republic: a category of countries most at risk from heat shocks. We analyze the effects of heat shocks on sovereign bond spreads, probabilities of default, and debt-to-GDP levels. A feature of structural models such as Mallucci (2022) is that they allow us to run micro-founded counterfactual analysis. This is done by running the model with the heat shock parameters turned off and comparing the outcomes to the baseline model where the heat shock parameters are turned on. The main findings from the sovereign default model are that in equilibrium heat shocks widen sovereign bond spreads by 66 basis points, increase the probability of default by 0.021, and lower debt-to-GDP levels by 5 percentage points as the bond market forces sovereign debt to more sustainable levels. The sovereign default model thus provides evidence that even a low mean and high uncertainty heat shock in the income process can inflict adverse financing conditions, as reflected in bond spreads, probability of default, and debt-to-GDP levels.

Next, we transition from a single-country analysis to our cross-country regressions. Using a panel of 76 countries spanning the years 1995–2017, the paper empirically tests the mechanisms of the sovereign debt model by investigating the effects of heat shocks on the outcomes of the sovereign default model, i.e. sovereign bond spreads, debt-to-GDP, and the probability of default. In addition, the regressions also test the assumptions in the income process of the sovereign default model. To this end, we first construct a heat shock variable in the vein of Marchiori et al. (2012) and employ this heat shock variable in a set

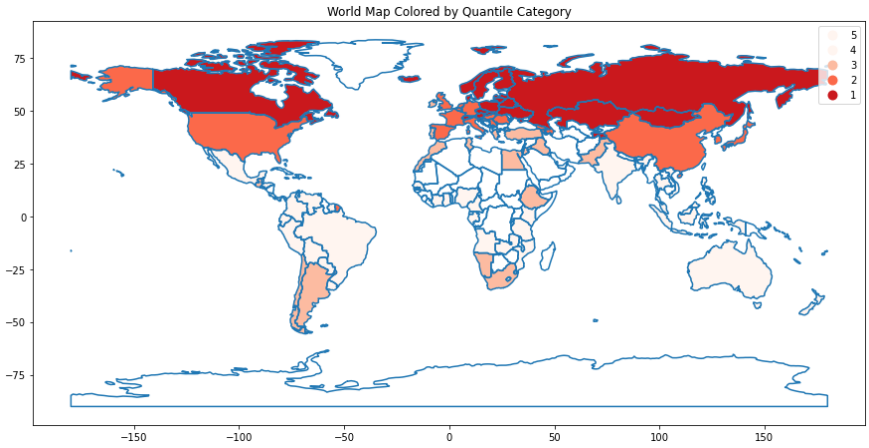


Figure 2: Difference in average temperature (1955–1965) and (2007–2017) by quantile for the country sample in the regressions. Deeper shades of red indicate higher temperature increases. Source: University of East Anglia Climate Research Unit

of regressions. The results from the empirical analysis are as follows.

In a univariate regression, a one-standard-deviation increase in the heat shock variable widens bond spreads by 0.60 basis points. Since the average country in our sample exhibits a within-country long-run temperature standard deviation of 0.45 °C, this implies an effect of approximately 1.3 basis points per °C above the long-run trend. This long-run mean already takes into account increasing temperatures as discussed in equation 1. This allows us to interpret the heatshock as a deviation above the expected temperature and it does expresses a level of uncertainty. Once we include country and year fixed effects alongside climate and macroeconomic controls, the coefficient rises to approximately 0.90 basis points, resulting in an impact of approx. 2 basis points increase in spreads per °C above the long-run trend. Once we add inflation, GDP growth and Debt-to-GDP only 1/3 of the direct effect remains. These three variables are the main transmissions channels through which heat shocks impact bond spreads. The direct effect of heat shocks, besides these channels, is only 0.8 basis points per °C increase.

When we split the sample into emerging and advanced markets, the direct impact of heat shocks is only significant for the EM subsample: a one-standard-deviation increase in the heat shock variable widens EM bond spreads by 1.7 basis points per °C increase. This results show that heat shocks are hitting mostly emerging markets. Regressions with CDS spreads corroborate this pattern, indicating that the widening carries a credit risk component. We interpret this heterogeneity through the lens of the sovereign default model: EM countries face greater variability in the heat shock variable, and bond markets price in this uncertainty. Finally, interacting the heat shock variable with agriculture's share of GDP reveals that EM countries with larger agricultural sectors are more vulnerable, consistent with agriculture serving as a transmission channel from the direct effect of heat shocks to sovereign risk.

When examining the other empirical results suggested by the sovereign default model,

we find that a one-standard-deviation increase in the heat shock variable lowers debt-to-GDP by 2.39 percentage points. This sign is consistent with the model's prediction that sovereigns reduce borrowing following adverse shocks. We find null results for real GDP growth, consistent with our characterization of heat shocks as low mean events that are insufficiently damaging to affect growth rates in our sample. For sovereign credit ratings, we find that the interaction of the heat shock variable with a post-Paris Agreement indicator is negative and significant, indicating that rating agencies penalized heat shocks more heavily once climate risk became more salient. Credit ratings serve as an alternative to measure default risks, other than using bond spreads.

A key message for policymakers is that climate change places unequal adverse effects on the sovereign bond market. Global warming leads to more challenging financing conditions for emerging markets compared to advanced markets. This is remarkable given that the current stock of CO_2-equivalent emissions which cause global warming mostly consists of emissions from advanced markets. As a result, policies need to be implemented to mitigate the externalities of climate change on emerging markets. Another dimension that policymakers need to take into account are the financing conditions of low-income countries (LICs). This category of countries is less developed than emerging markets and faces even larger hurdles when financing the adverse effects of heat shocks. It is beyond the scope of this paper to study the effects of heat shocks on LICs, as these countries often lack access to the international sovereign bond market and hence bond yields are not observable. But it is reasonable to expect that the adverse effects of heat shocks are an order of magnitude larger for LICs.

The paper proceeds as follows. Section 2 presents the literature review. Section 3 describes the data sources and presents summary statistics. Sections 4, 5, and 6 outline the sovereign debt model and present the outcomes of our theoretical framework. Section 7 shows the empirical results and delves into heterogeneity analysis. Lastly, Section 8 concludes.

2 Literature Review

Our paper is situated in the literature on uncertainty and its impact on sovereign spreads and CDS. Earlier theoretical work by macroeconomists dealt with uncertainty by considering self-insurance through precautionary savings (Leland, 1968; Carroll, 1997; Hubbard (1997)). These models link saving behavior to borrowing constraints and its impact on aggregate outcomes when future income streams are uncertain. In the finance literature related work has explored how uncertainty shapes bond and CDS spreads by influencing borrowing conditions and default risks (Johri et al., 2022; Bok et al., 2025; Cuadra and Sapriza, 2008).

This paper connects these two strands of literature through climate change as a key source of uncertainty, as climate change impacts both the financial and macroeconomic environment. See also the recent attention found in literature (Klomp, 2015; Barnett, 2020; Beirne et al., 2021; Cappiello et al., 2023). This literature explores theoretically and empirically, how uncertainty due to climate change affects macro and financial outcomes.

While climate change and rising temperatures are anticipated, the variability in the rise of temperature is uncertain. This uncertainty affects borrowing behavior from the sovereign and the lending behavior from the financial market, where financial markets want to price in this uncertainty through risk premia as in Seltzer et al. (2020) and sovereigns want to self-insure through saving or borrowing.

Klomp (2015) analyzes the effect of large-scale natural disasters on sovereign risk in emerging economies. Using the International Disaster Database (EM-DAT) of Guha-Sapir and D'Aoust (2011), the study identifies 380 severe disaster events across 40 countries between 1999 and 2010. These data are matched with monthly sovereign CDS spreads, yielding a high-frequency panel well suited to capture short-term dynamics. Klomp (2015) uses a pooled mean group estimator, which allows country-specific short-run effects, but imposes homogeneity in the long-run relationship. Barnett (2020) computes the social cost of carbon by incorporating climate risk uncertainty, ambiguity over probability models and uncertainty about the damage function and finds that these sources of uncertainty are associated with elevated levels of the social cost of carbon. Beirne et al. (2021) find that climate vulnerability has stronger adverse effects on bond yields compared to climate resilience and that the adverse effects on bond yields are not only temporary, but become permanent after 18 quarters with the most pronounced effects for the most vulnerable countries. Cappiello et al. (2023) find that credit rating agencies are incorporating climate risk following the Paris Agreement and that physical risk such as heat shocks and other natural disasters are associated with lower sovereign credit ratings.

A paper particularly close to ours is Seltzer et al. (2020), who examine the effects of regulatory uncertainty on bond credit ratings as well as bond and CDS spreads by using the Paris Agreement as a regulatory shock. They show that bond spreads of US carbon-intensive firms widened significantly. By estimating a structural Merton model, the authors demonstrate that this widening of bond spreads was not due to a decline in firm asset values, but rather due to an increase in asset volatility, which in turn increased probability of default. The rise in probability of default stemmed from increased uncertainty on future regulatory costs.

Within the sovereign default literature, Mallucci (2022) provides a seminal contribution by incorporating a disaster risk parameter in the income process of a sovereign default model. He shows that both macro and financial outcomes are adversely impacted following hurricane disasters for small-open economies representing a high mean, but low uncertainty shock. Our paper contributes to the climate change literature by calibrating the sovereign default model to the case of a low mean impact and high uncertainty shock i.e. a heat shock and tracing out the heterogeneity in a regression framework. We focus on calibrating to heat shocks, because unlike hurricanes, they represent a global phenomenon, thereby affecting a larger cross-section of countries.

3 Data and Descriptive Statistics

Several data sources are used in the analysis for the sovereign default model and the empirical analysis. The final dataset covers 76 countries spanning a period between 1995 - 2017. We obtain dollar denominated bond yields from bonds in the JP Morgan Emerging Market Bond Index Global (EMBIG), while for the advanced economies the 10-year local currency bond yield is obtained from Bloomberg[1]. Bond spreads are computed relative to the US 10-year Treasuries. Country-level temperature and precipitation data are obtained from the Climatic Research Unit from the University of East Anglia. Macroeconomic and financial variables are obtained from the IMF's International Financial Statistics (IFS) and the World Bank's World Development Indicators (WDI) database.

To construct our heat shock variable we follow the temperature anomaly variable of Marchiori et al. (2012), where the heat shock is computed as the deviation of the mean annual temperature from the long-term mean of temperature, divided by the long-run standard deviation of temperature:

$$Heat\ shock_{i,t} = \frac{Temperature_{i,t} - \mu_i^{LR}(Temperature)}{\sigma_i^{LR}(Temperature)} \tag{1}$$

Where $Temperature_{i,t}$ is the mean annual level of temperature measured in degrees Celsius in country i in year t, and $\mu_i^{LR}(Temperature)$ is the expanding mean of temperature. We use an expanding mean to capture the expected component of climate change. Similarly $\sigma_i^{LR}(Temperature)$ is the long run standard deviation of temperature. In both the mean and the standard deviation the superscript LR denotes the expanding mean inherent to the upward trend in global warming. Comparing the current temperature to a long-run mean allows us to capture the heat shock. Scaling the numerator by the standard deviation allows us to compare countries with different climates. To compute the long-run mean and standard deviation of temperature we use an expanding window starting from 1901 - 1995, which expands until 2017. Histograms of the heat shock variable are shown in figure 3 after aggregating across countries and over time. This figure clearly shows the uneven distribution of heat shocks between EM and AM.

As expected in a world with climate change, the heat shock variable has a positive mean and is right skewed with a long fat tail. The standard deviation of our heat shock variable captures the uncertainty in future income streams that governments face. This means that over the period 1995-2017, the world has experienced positive temperature anomalies with temperature anomalies as large as almost two times the historical long run standard deviation as seen in table 1. Table 11 and 12 show the summary statistics for the AM and EM sample, where table 11 and 12 show that the mean and standard deviation of heat shocks are higher in EM compared to AM. This is also reflected in figure 3. Figure 4 and 5 show the heat shock varies over time. When we fit a non-parametric regression on the data we observe that the level of heat shocks are higher in EM than AM countries. In addition,

[1]As a robustness check we included the real effective exchange rate as a control, it does not alter our results.

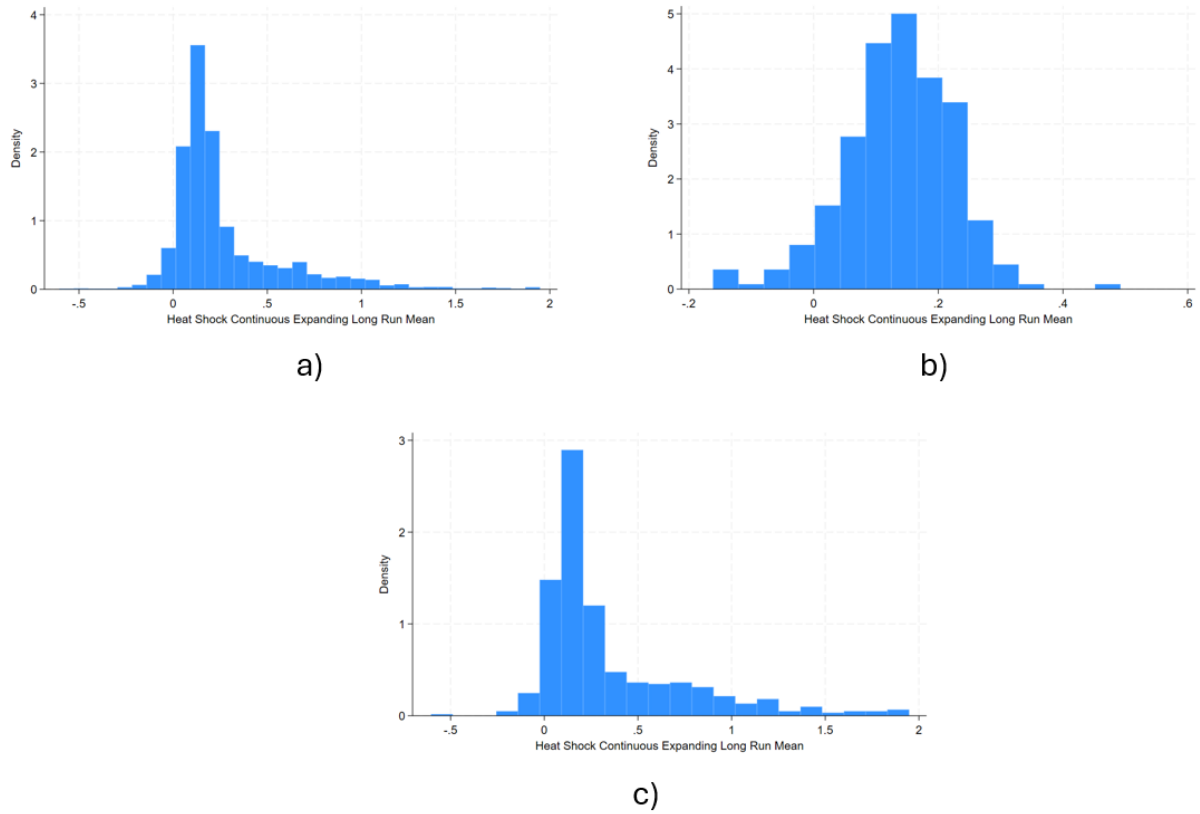


Figure 3: Heat shock densities for a) the full sample, b) AM sample and c) EM sample. The heat shock densities are computed following equation 1.

temperature variability has steadily increased for EM only, this increased band directly indicates the increased uncertainty of heatshocks. Conversly, the band of AM heat shocks has remained constant, indicating no increase in uncertainty over time.

The descriptive statistics described here give enough indication to investigate further the role of uncertainty and heat shocks. In the next section, we investigate the role of uncertainty by creating a theoretical framework that explains the core traits of heat shocks we are interested in, namely (i) low mean impact shock, and (ii) high uncertainty on the size of the shock. Later in this paper we compare the theoretical results to an empirical counterpart.

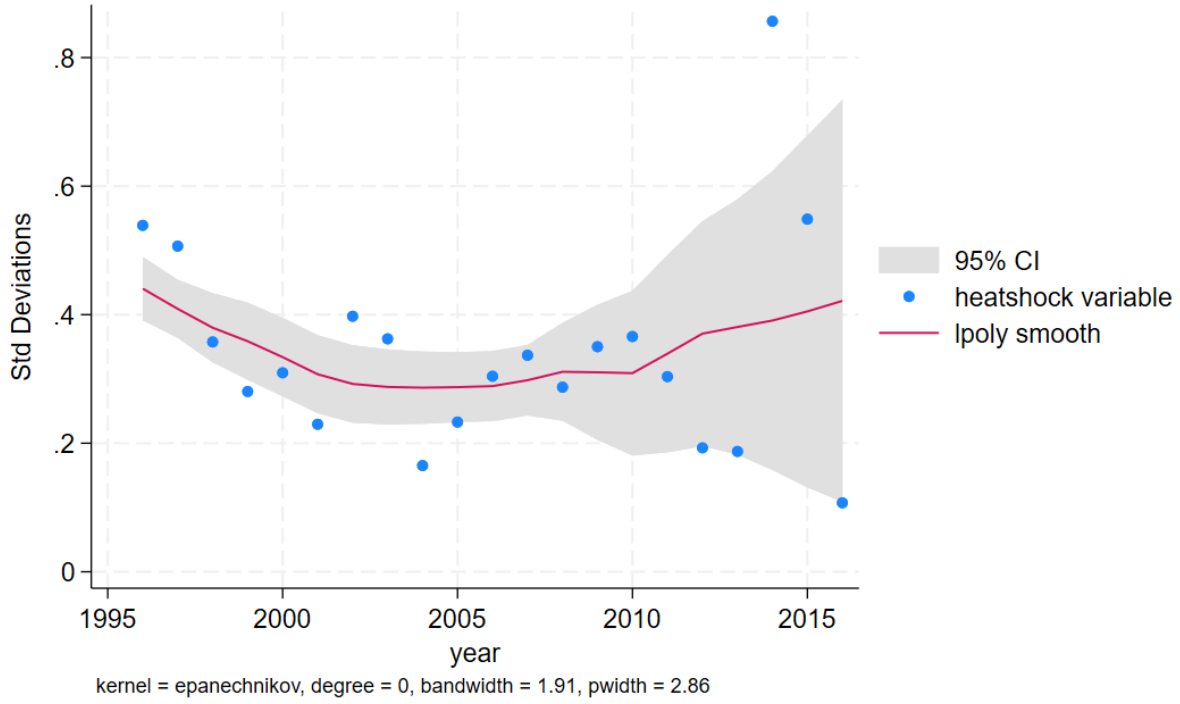


Figure 4: Non-parametric regression of the heat shock variable in equation 1 over time for EM countries.

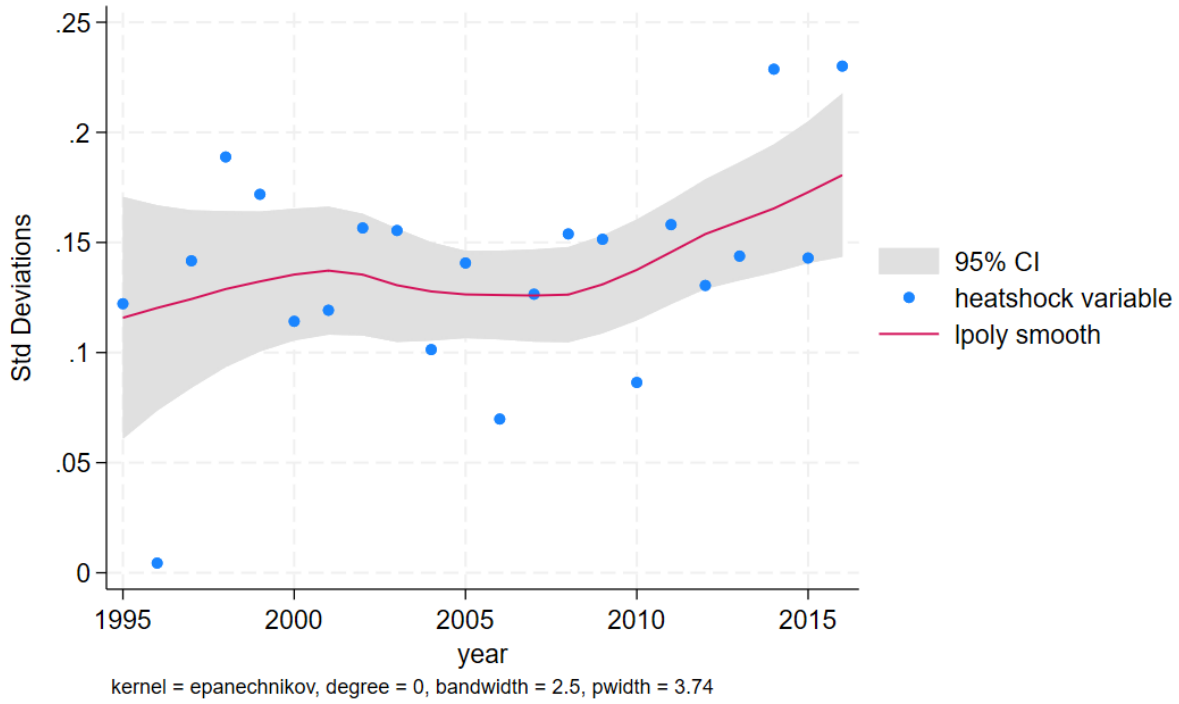


Figure 5: Non-parametric regression of the heat shock variable in equation 1 over time for AM countries.

Table 1: Summary Statistics - Full Sample

Variable	Obs	Mean	Std. Dev.	Min	Max	Source
Δ Bond Spreads	893	-0.098	2.835	-25.013	42.358	Bloomberg
Δ CDS Spreads	376	0.035	1.894	-13.069	16.032	Bloomberg
Heat Shock	893	0.260	0.318	-0.605	1.948	CRU
Heat Shock Truncated	893	0.264	0.313	0.000	1.948	CRU
Precipitation	893	90.821	56.794	0.936	298.352	CRU
Δ Fitch Credit Ratings	755	-0.279	1.147	-10.000	4.000	Fitch
Δ Ln(Reserves)	893	0.032	0.254	-1.672	2.523	IMF
Inflation CPI	893	4.676	5.073	-0.418	25.000	IMF
Debt-to-GDP	893	57.282	26.140	14.976	164.377	IMF
Δ Debt-to-GDP	893	1.315	10.264	-12.349	31.440	IMF
ND Readiness Index	893	49.999	17.145	17.371	80.192	ND-Gain
Terms-of-Trade	893	106.947	24.834	55.195	264.204	WDI
Real GDP Growth	893	3.149	3.352	-11.991	17.048	WDI
Ln(GDP constant prices)	893	5.582	1.353	2.372	9.326	WDI
Agriculture Output-to-GDP	893	6.926	6.398	0.214	38.983	WDI

Note: Spread changes are the annual first difference in spreads. The heat shock variable is constructed as in equation 1 and is computed as the deviation of annual temperature with the long run temperature (expanding window 1901-1995) scaled by the long run standard deviation of temperature (expanding window 1901-1995). Precipitation is defined as annual precipitation in millimeters. ND Readiness Index is the Notre Dame Readiness Index. Δ ln(reserves) is the log first difference of foreign currency reserves over GDP, where non-domestic currency is converted to the USD. Δ Fitch Credit Ratings is the annual first difference of the country's Fitch credit rating, where the rating is converted to a 21 points scale. Higher values indicate stronger creditworthiness. Agriculture Output-to-GDP is the share of agriculture in the GDP. GDP growth, CPI Inflation, Debt-to-GDP, Budget Balances and Terms-of-Trade are winsorized at the 5% level.

Table 2: List of variables and definitions

Variable	Definition
Bond Spread Change	First difference of the spread expressed as the yield differential between the bond and the 10Y US Treasury
10Y CDS Spread Change	First difference of the spread expressed as the yield differential between the bond and the 10Y US Treasury
Heat Shock	In standard deviation units, following equation 1
Precipitation	Millimeter precipitation per year
Notre Dame Readiness Index	ND-GAIN climate change readiness index
Real GDP Growth	Annual percentage change, obtained from GDP at constant prices using the expenditure approach
CPI Inflation	Percentage change, CPI inflation
Debt-to-GDP	Percentage points, nominal general government gross debt over nominal GDP
International Reserves	Log first difference of international reserves in USD dollar terms scaled by real GDP
Terms-of-Trade	Terms-of-Trade Index
Fitch Credit Ratings	First difference of the country's Fitch credit ratings converted to a 21-point scale; higher values indicate stronger creditworthiness
Agriculture Output-to-GDP	Share of agricultural output over GDP

Note: The table shows the definitions of the variables used in the paper.

4 Sovereign Debt Model

4.1 General set-up

Our framework extends the sovereign debt model of Arellano (2008) by introducing heat shocks that affect output dynamics. We follow Hatchondo and Martinez (2009) by using long-term bonds. This is parallel to the work of Mallucci (2022) using hurricane shocks. In this section we use a subcase of Hatchondo and Martinez (2009) by setting the maturity of the bonds to 1 period, effectively turning long-term bonds into yearly bonds. Removing this complexity allows us to more clearly and directly explain the mechanism behind the sovereign default model. In the next section 4.2 we discuss the optimization problem of the key actors under the full complexity of the model.

4.1.1 The government

The economy is modeled as an iterative game between two players: the government and the international financial market. The iterative actions of both players determine the equilibrium interest rate, default probability, and debt dynamics.

The government is a benevolent policymaker who maximizes the expected lifetime utility of households with utility depending only on consumption c. Households face stochastic income y and have no access to insurance markets to smooth consumption. Their consumption is subject to the following:[2]

$$c = y + qb' - b \tag{2}$$

Where y is the income of households, q is the bond price and b is the repayment of debt. We can rewrite this constraint in the following manner to split up expenses and income streams:

$$c + b = y + qb' \tag{3}$$

On the Left-Hand Side (LHS) we find all the expenses, with c being the consumption of households and b being the outstanding debt. On the Right-Hand Side (RHS) we find all the income streams, with income y and new debt b' being issued at price q.

4.1.2 The financial market

Since our theoretical model is an iterative game between two players, the financial market is not passive, and it adjusts its behavior to new information. While the government, as a benevolent planner, is risk-averse, the financial market is risk-neutral and sets bond prices in such a way that expected profits are zero, accounting for the probability of default d' in the next period from the government and the risk-free interest rate r^{RF} :

$$q = \frac{1 - d'}{1 + r^{RF}} \tag{4}$$

[2]Written in prime notation commonly found in the literature: the current state of a variable is denoted without a prime symbol (e.g. $y_t \equiv y$) and the state of the variable in the next period is denoted with a prime symbol (e.g. $y_{t+1} \equiv y'$).

When the government defaults, it is temporarily excluded from the financial market for an expected duration of $1/\lambda$ periods and faces an output loss, which results in lower income $y^{default} \leq y$. During this time, the government cannot borrow or lend, limiting consumption to $y^{default}$.[3]

In line with Mallucci (2022) and Hatchondo and Martinez (2009) we assume that defaults entail an output loss. This output loss captures the disruptive effect of defaults on economic activity. Hatchondo and Martinez (2009) offer three explanations: First, sovereign default increases the borrowing cost of domestic firms. These borrowing cost increases raise prices and lower spending. Second, foreign credit to domestic firms is greatly reduced when sovereigns default (Arteta and Hale, 2008). The restriction of credit hinders the expansion of existing firms and the entry of new firms. Third, disruptions in debt payments cause a decrease in aggregate productivity (Kobayashi, 2006).

A final note on the financial market is the link between the bond price q and the interest rate that sovereigns pay. The bond price q and the interest rate r governments pay are inversely related to each other:

$$q = \frac{1}{1+r} \tag{5}$$

By combining the two expressions for q, we can retrieve an expression for the spread in terms of the default probability:

$$spread = \frac{1}{1-d'} - 1 \tag{6}$$

The spread is a measure of the risk premium that financial markets impose in order to finance the debt of the government. As default probabilities increase, financial markets will want to compensate for potential defaults by increasing the risk premium.

4.1.3 The solving algorithm

Figure 6 below summarizes the sequence of events that are repeated until an equilibrium is reached. This diagram is also a visual representation of the solving algorithm. At each iteration the outcomes for two players are calculated and the differences in the outcomes between the current and the previous iteration are stored. When the differences are smaller than a tolerance parameter (e.g. 1e-6) we stop the algorithm. We conclude that an iterative equilibrium has been achieved since neither the government nor the financial market changed their behavior since the last iteration.

The government begins each period observing household income y and outstanding debt b. It decides whether to repay or default on this obligation, based on which action maximizes the discounted lifetime utility of households.

If it repays, it chooses next period's debt b', anticipating both the bond price set by financial markets and the expected future income. It will need to refinance its future debt obligations and the consumption, but takes into account the price of debt and the future income of households.

[3]Where λ is defined as the probability to be readmitted to the financial market

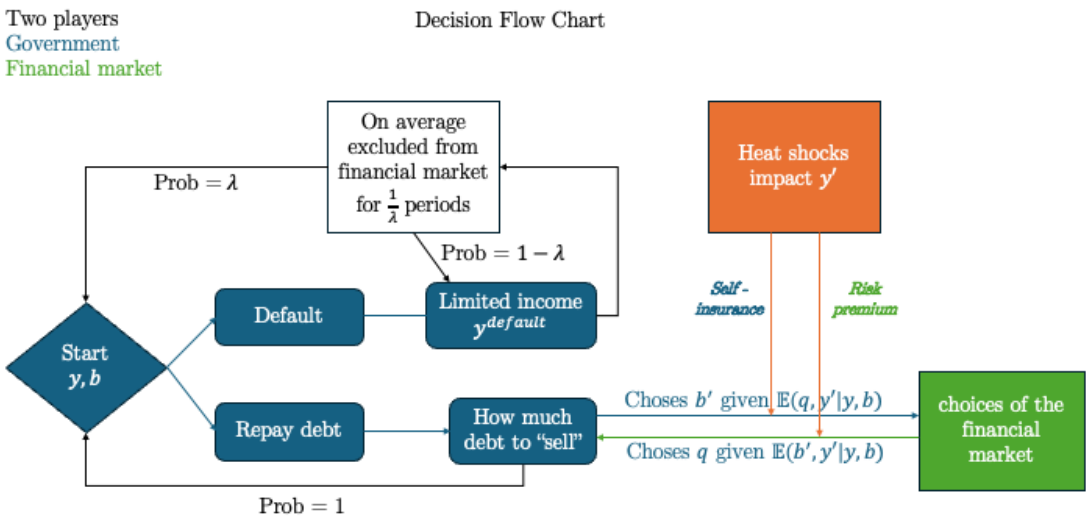


Figure 6: Flowchart showing the iterative process the government and the financial market go through to achieve a stable iterative equilibrium.

If it defaults, income falls to $y^{default}$ and the economy is temporarily excluded from bond markets. When defaulting there is a probability λ that the government is readmitted to the international financial market, which leads the government to return to the start point in our diagram but without debt.

4.1.4 How heat shocks impact market outcomes

As can be seen in Figure 6, heat shocks impact the model through the income process of households. Income is modelled as a log-normal AR(1) process:

$$\log y' = \rho log y - \xi\ h + e^y \tag{7}$$

Where income has some persistence ρ, but is subject to a heat shock h, and an idiosyncratic income shock e^y. When hit by a heat shock, the indicator term ξ becomes 1, and income is reduced by h units.

$$h \sim N(\mu_h, \sigma_h)$$
$$e^y \sim N(0, \sigma_y)$$

Both shocks have persistent effects through the AR(1) process, meaning that both idiosyncratic endowment shocks and heat shocks affect income for several periods. It is against this period of low income that the government wants to insure itself by selling bonds to the financial market. By selling government bonds b, the government tries to smooth consumption of households and to protect them from a series of low income draws.

To understand the impact of heat shocks in our theoretical model we need to recognize the three components of heat shocks:

- The probability of being hit ξ
- The mean loss of income μ_h
- The uncertainty on the loss of income σ_h

Process h is normally distributed and thus allows positive income effects of heat shocks, though these are rare in our simulations.[4]To demonstrate, we start from a world without heat shocks and in equilibrium. Heat shocks are introduced at time t=1. At time t=0 both players change their behavior as their expectations have been altered. Expected income is now $\xi\mu_h$ lower than before the introduction of heat shocks.

The financial market sees this loss of expected income and raises the risk premium for new debt as it recognizes that lower income streams increase the probability of default in the future. Likewise, the government adjusts its expectations on future income and wants to increase debt for any given level of interest rate so it can smooth consumption. Additionally, the government also changes its probability of default. It shifts the probability of default so as to maximize the expected lifetime utility of households. Since the expected income streams change with heat shocks, the probability of default also changes.

Both players try to anticipate the other's actions for several iterations. As the choice of one player affects the action of the other player, it can take many iterations before their actions become stable over time. The equilibrium is found when both players do not deviate in actions from the previous iteration.

4.1.5 Heat shocks versus hurricane shocks

We distinguish ourselves from Mallucci (2022) by focusing on the uncertainty in heat shocks. The mean impact of a heat shock is quite modest, but heat shocks have fat tails. In the literature this is often referred to as black swan events. The iterative nature of our theoretical model takes into account these fat tails as the model takes random draws from the distribution at every iteration.

Focused on the Dominican Republic we see that the mean loss caused by hurricanes is about 0.104% of GDP, while the mean loss of heat shocks is only 0.005% of GDP. However, heat shocks have fatter tails than hurricanes and this will impact the market differently. While the mean loss is about 20x higher in the case of hurricanes, we see that there is about 3x smaller standard deviation in damages caused by hurricanes.[5]

[4]The normal distribution for climate shocks is also adopted by Mallucci (2022) in the context of hurricanes. Unlike hurricanes, however, positive income effects of heat shocks have empirical support, making the normal distribution a more natural fit for our setting. Mallucci (2022) notes in footnote 9 that positive hurricane realizations are a distributional artefact and shows via robustness analysis that their quantitative importance is negligible.

[5]To clarify, this is the case of the Dominican Republic. Heat shocks and hurricanes have different distributions depending on the geographical location.

Given that these models run for thousands of iterations, these unlikely events do occur and alter the behavior of both players. Financial markets will adjust the risk premia to cover the possible losses by these black swan events. Governments will want to insure against the potential enormous losses by selling debt to offset the income loss.

4.2 The optimization problem

Now that we have explained the basic algorithm behind our model, we can reintroduce the model complexity by allowing bonds to last for several periods, i.e. $\psi < 1$. Following Hatchondo and Martinez (2009) we use ψ to fix the average maturity of the bond portfolio. When $\psi = 1$, we have one period bonds, at the other extreme when $\psi = 0$ we get perpetual bonds. By setting the maturity parameter between 0 and 1, we can retrieve the average maturity on government bonds. As ψ is a fraction, after every period a fraction ψ of outstanding debt has matured.

As bonds do not mature in one period, b takes a more nuanced interpretation. We follow Hatchondo and Martinez (2009) and use outstanding coupon payments b to track the debt levels of the government.[6] Timing is of importance, b represents the outstanding coupon payments at the beginning of the period. Hatchondo and Martinez (2009) assume that a fraction of the debt matures at a rate ψ. In coupon terms this means that at the end of the period, ψb of coupon payments have matured.

The remainder $(1-\psi)b$ of coupon payments have not yet matured, and are transferred to the next period. The coupon payments in the next period b' are thus composed of coupons that have not yet matured $(1-\psi)b$ and additional coupons payments, i.e. additional debt.

We now introduce the full notation of all the constraints and objective functions discussed earlier. This part is fully analogous to Mallucci (2022).

4.2.1 The government

The government wants to maximize the discounted expected lifetime utility of households, with β being the discount factor at which future utility is discounted. The associated CRRA utility function takes the following form:

$$U(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{8}$$

With γ denoting the degree of relative risk aversion.

The optimization problem for the government can be seen as a set of three dynamic programming problems that are linked. In each period, a government with access to the financial market has to decide on paying out coupons and matured debt or to default on its obligation. Its default decision d maximizes the following:

$$V = \max_{d}\{(1-d)\,V^{nd} + d\,V^{d}\} \tag{9}$$

Where V^{nd} and V^{d} are the value functions of the households associated with the non-default and default scenario respectively. As the choice to default d is binary, the overall value function V will be either V^{nd} or V^{d}. The government needs to consider the associated

[6] Debt is defined as the present discounted value of coupon payments: $B = \frac{b}{r^{RF}+\psi}$

value functions of both scenarios and chooses d to maximize households discounted lifetime utility. It does this by separately solving the optimization problems for the default and the non-default cases, and then comparing the associated value functions of these sub-problems.

The value function V^{nd} describes the household's present discounted maximum expected utility in the case of non-default. It is the solution to the following problem:

$$V^{nd}(y,b,h) = \max_{c,\ b'} U(c) + \beta \mathbb{E} V(y',b',h') \tag{10}$$

subject to the following budget constraint:

$$c = y + q(y',b',h')[b' - (1-\psi)b] - b \tag{11}$$

Household utility comes from consumption in the period itself and the discounted expected maximum utility from the next period onward. The latter will depend on next period's income y', if a heat shock h' occurs, and the new outstanding debt obligations b' if the government repays in the current period. The details of the income process can be found in the previous section.

We can rewrite the budget constraint in the following manner to separate expenses and income streams:

$$c + b + q(y',b',h')(1-\psi)b = y + q(y',b',h')b' \tag{12}$$

On the LHS we have consumption c, outstanding coupon payments b and the term $(1-\psi)b$, which are the coupon payments that will not mature in the next period. The last term $q(y',b',h')(1-\psi)b$ denotes the present discounted value of the remaining coupon payments. On the RHS we have the current income y and the possibility to accrue new debt $q(y',b',h')b'$.

The value function V^d describes the household's present discounted maximum expected utility in the case of defaulting on debt. It is the solution to the following problem:

$$V^d(y,0,h) = U(c) + \beta \mathbb{E}[(1-\lambda)V^d(y',0,h') + \lambda V(y',0,h')] \tag{13}$$

subject to:

$$c = y^{default} \tag{14}$$

Utility comes from consumption in this period and the discounted maximum utility from the next period onward. The future is discounted and weighted by its probability to occur. When defaulting on debt, international markets exclude the government from financing its debt. The discounted maximum utility of the future takes into account that there is a $1-\lambda$ probability to remain excluded from the markets and thus attain $V^d(y',0,h')$ in the next period. There is, however, also a probability λ to be readmitted to the financial market and thus attain $V(y',0,h')$, but now without any debt.

Following Arellano (2008), we state that income gets reduced to $y^{default}$ when excluded from the international financial market, where $y^{default}$ depends on the level of income that is achieved:

$$y^{default} = \min\{y, \delta \mathbb{E} y\} \tag{15}$$

Similar to Arellano (2008), we model output costs to be asymmetrical and increasing in endowment realizations. Output costs can be low to zero in bad times, i.e. when the economy is hit by a negative endowment shock and income is very low. In good times, however, when income is high, output costs can be large. As stated by Arellano (2008), the asymmetrical approach allows us to make output costs less sensitive to income shocks.

4.2.2 The financial market

As explained in the previous section, financial markets are risk neutral and this is reflected in the bond price. Investors buy sovereign bonds, but set the bond price by taking into account the expected future income stream y', the probability of default d' and heat shocks h' in such a way that expected profits are zero, while discounting by the risk-free interest rate r^{RF} :

$$q(y', b', h') = \frac{1}{1 + r^{RF}} \mathbb{E}\left[(1 - d') + (1 - \psi)(1 - d')\, q'\right] \tag{16}$$

Where the first term within the expectations $(1 - d')$ are the current coupon obligations when the government repays its debt. The second term $(1 - \psi)(1 - d')$ is the present discounted value of the coupon payments that will not mature at the end of the period.

5 Parameterization

The model is calibrated to reproduce key financial moments of the Dominican Republic, a small open economy that has access to a liquid international sovereign bond market. Being integrated in the international financial market is required to correctly examine the impact of heat shocks on defaults, debt and spreads. As the Dominican Republic is part of the JP Morgan Emerging Market Bond Index Global, we see this as a sufficient condition of its embeddedness in international finance.

Parameters taken from Mallucci (2022)		
Moment	**Value**	**Source**
Relative risk aversion	$\gamma = 2$	Standard
Readmission probability	$\lambda = 0.33$	Richmond and Dias (2009)
Risk free rate	$r^{RF} = 0.0451$	US T-Bill

Table 3

We first report the parameters that are taken directly from Mallucci (2022) and are shown in table 3. The moment matching exercise of Mallucci (2022) covers several countries and table 3 presents the parameters that are identical among all countries. The model

employs a CRRA utility function, where the relative risk aversion γ is set equal to 2, which is standard in the literature. Next, we use data from Richmond and Dias (2011) to retrieve the mean exclusion time from financial markets. Taking its inverse gives us the readmission probability λ. Lastly, the risk free interest rate is set at 0.0451 matching the average T-bill rate from 1980 to 2019 following Mallucci (2022).

Similar to Mallucci (2022) we also employ country specific parameters. These country specific parameters for the Dominican Republic are reported in table 4. These parameters can be broken down into imposed parameters and calibrated parameters.

Table 4: Parameters for the moment matching exercise - Dominican Republic

Imposed and calibrated parameters		
Moment	**Value**	**Source**
Duration	$\psi = 0.1731$	Average Maturity
Heat shock frequency	$p_h = 0.083$	CRU
Income autocorr.	$\rho_y = 0.88$	WDI
Income st. dev.	$\sigma_y = 0.0464$	WDI
Heat shock mean loss	$\mu_h = 0.0006$	WDI
Heat shock loss st. dev.	$\sigma_h = 0.41$	WDI
Moment	**Value**	**Target Statistics**
Discount factor	$\beta = 0.897$	Debt/GDP
Output cost	$\delta = 0.798$	Mean Spread

Note: the table reports the country-specific parameters for the Dominican Republic that are used for the calibration of the model, and the associated target statistics. The discount factor and the output cost parameter are jointly calibrated to match the average spread level and the average debt-to-GDP ratios.

We follow the same approach as Mallucci (2022) to fix the imposed parameters. The only difference is that we use information on heat shocks from the Climate Research Unit (CRU) of the University of East Anglia and the World Development Indicator (WDI) database. All the imposed parameters are presented in the top part of table 4. Heat shocks in the theoretical model are binary events, therefore we need to transform the temperature data into binary points. We define heat shocks when temperatures within a 3-month window are 2 standard deviations higher than their long run mean. The frequency of these shocks leads us to set $p_h = 0.083$, which means that the Dominican Republic is hit by a heat shock once every 12 years.

For the remaining parameters that are imposed, we regress an AR income process to retrieve the parameters using detrended log GDP data from the WDI between 1980 and 2019. Income persistence ρ_y is taken directly from the autoregressive coefficient. $\sigma_y$is the standard error of the regression errors. Lastly, the impact of heat shocks is retrieved by

Table 5: Results of the moment matching exercise

Quantitative analysis of Dominican Republic			
Panel A - Own results			
Moment	Moments from the data	Simulated moments With heat shocks	Simulated moments No heat shocks
Average spread basis points	481	484	415
Debt-to-GDP	0.25	0.25	0.30
Heat shock frequency	0.083	0.086	-
Default frequency	0.051	0.091	0.072
Panel B - Results from Mallucci (2022)			
Moment	Moments from the data	Simulated moments With hurricanes	Simulated moments No hurricanes
Average spread basis points	481	479	416
Debt-to-GDP	0.25	0.25	0.29
Hurricane frequency	0.051	0.048	-
Default frequency	0.051	0.083	0.074

Note: the table reports moments obtained from simulating the model economy for 10 000 periods with and without heat shocks. In the model economy with and without hurricanes, we follow Mallucci (2022) and simulate the model for 9500 periods.

introducing a heat shock dummy as defined in the previous paragraph. The point estimate of the dummy gives us the mean loss of heat shocks μ_h and its standard error gives us σ_h.

The calibrated parameters are found at the bottom of table 4. We jointly estimate the discount factor β and the output cost δ to match both the average debt-to-GDP and the average mean spread of the Dominican Republic between 1980 and 2019.

6 Quantitative Analysis

Table 5 shows the key moments of the Dominican Republic relevant to our model. We compare moments from the data with simulated moments from our calibration. This comparison allows us to see how well the model fits the data. Next, we compare simulated moments with heat shocks and simulated moments from a no-heat shocks counterfactual. The model closely tracks the average spread and the debt-to-GDP that we used as targets for our calibration.

As our model fits the moments from the data, we can use the baseline calibration to compare the heat shocks simulation to a counterfactual simulation without heat shocks.

This exercise allows us to measure the effect of heat shocks on spreads, debt-to-GDP and the default frequency. The impact on spreads is remarkable, when heat shocks are absent spreads are 78 basis points lower, indicating better financing conditions. Better financing conditions allow the government to refinance existing debt, accrue more debt, and most importantly make defaulting on existing debt less likely.

This in turn also explains why debt-to-GDP is higher when no heat shocks are present. Looking at table 5, we find a 5 percentage point increase in debt-to-GDP. To understand the increase in debt levels we need to account for the fact that the model does not allow any form of partial debt relief. Either debt is repaid or it's fully defaulted. In a world with heat shocks, defaults occur more often leading to zero debt in the following period. The average debt as a result will be lower compared to a situation with lower default probability. Stated differently, governments optimal debt levels might be higher if they were not constrained by high risk premia. Heat shocks, however, push governments into defaults sooner, pushing sustainable average debt levels down.

6.1 Default probabilities

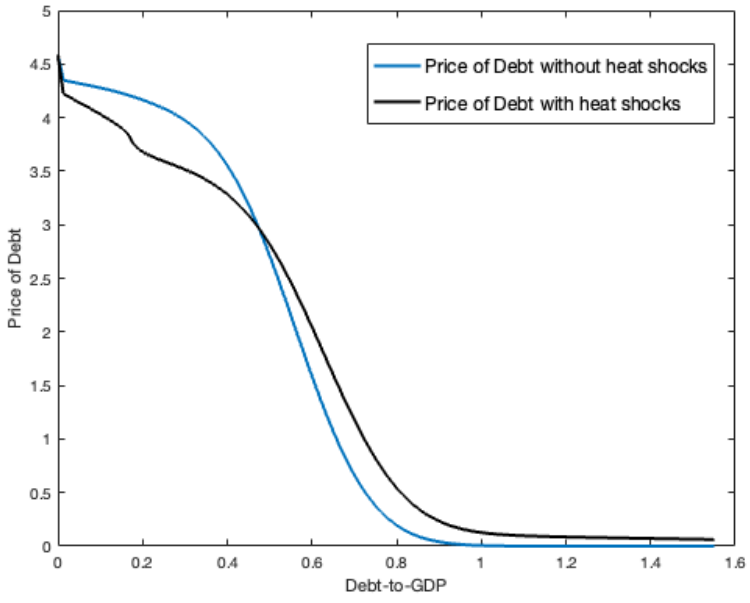


Figure 7: This graph plots the bond yield (debt price) as a function of debt-to-GDP. It gives an indication of the financing conditions of governments, where lower bond yields (higher debt prices) are more favorable to finance debt. See also equation 5, where interest rates are inversely related to debt prices.

Figure 7 allows us to better understand why debt levels fall when heat shocks are present. When the heat shock parameter is turned on, governments would like to borrow more to cushion future income losses. How much they can borrow, however, depends on the

bond yield, and therefore on the risk premium. Higher spreads make borrowing more expensive, so governments demand less debt. This is the price effect, visible in Figure 7: at relatively low debt levels, the bond price q already declines i.e. downward sloping demand curves.

Risk-neutral pricing by the financial market disciplines governments and constrains default events. Debt is the government's only instrument to smooth the temporary drop in income caused by heat shock. While large "black swan" heat shocks are rare, when they occur they sharply raise the debt of governments. If the government were to default immediately afterwards, its outstanding debt would disappear. The negative income effects, however, would continue to reverberate because of the income AR(1) process as shown in equation 7. Risk-neutral investors reflect this directly in the bond price by keeping bond yields elevated. Default therefore becomes less attractive, and the unconditional probability of default is constrained. In Figure 7 this shows up as a flatter slope of the heat shock pricing curve compared with the no heat shock case.

In contrast, in normal times when heat shocks are not black swan events, shocks have a limited impact on income. Because the risk premium is already higher at low debt levels, the consumption available after default may exceed the consumption levels when repaying. In these cases, default becomes the preferred option.

6.2 The impact of uncertainty

Table 6: The impact of uncertainty

Quantitative analysis of Dominican Republic			
Moment	Heat shocks (1)	Heat Low uncertainty (2)	No Heat shocks (3)
Average spread basispoint	484	406	415
Debt-to-GDP	0.25	0.30	0.30
Heat shock frequency	0.086	0.082	–
Default frequency	0.086	0.072	0.072

Note: the table reports moments obtained from simulating the model economy for 10 000 periods with (i) with heat shocks with the heat shock uncertainty parameter σ_h turned on (ii) with heat shocks with the heat shock uncertainty parameter σ_h set very low and (iii) no heat shocks.

To examine the uncertainty channel, we keep all model parameters constant except for the standard deviation of heat shocks. We set $\sigma_h = 0.001$. In this scenario, the mean impact of shocks remains the same, but black-swan events become impossible. Table 6 presents the full model with heat shocks in the first column and compares it with the low-uncertainty scenario (i.e. $\sigma_h = 0.001$) in the second column, as well as with the no heat shock counterfactual.

We obtain a clear result: most of the impact of heat shocks operates through the uncertainty channel. While the average spread is marginally lower in column (2), the debt-to-GDP and default frequency moments are identical when compared to the no-heat shock counterfactual of column (3). Spreads rise because of uncertainty about future repayments of existing debt. Financial markets respond by increasing risk premia, which in turn leads governments to default more frequently and accumulate less debt.

One important remark is that our model concerns only equilibrium outcomes. This means we compare steady states and do not account for transitional dynamics or different channels. In contrast, the empirical analysis in the next section will allow us to distinguish between the direct and the indirect effects of heat shocks.

7 Empirical Analysis

The preceding sections established that disaster shocks characterized by a low mean and high uncertainty, such as heat shocks, deteriorate both macroeconomic and financial outcomes, as reported in Table 6. In the model, a shock of this form is sufficient to (i) widen sovereign bond spreads, (ii) raise the equilibrium probability of default, and (iii) lower equilibrium debt levels, as borrowing becomes prohibitively costly and the sovereign retreats from international capital markets.

The structural model delivers a general equilibrium and counterfactual analysis for a single economy, i.e. the Dominican Republic. To disentangle how and in which countries heat shocks affect macroeconomic and financial outcomes, we turn to our empirical strategy using panel regressions. In our data and descriptive statistics section we already see a pattern that EM countries are facing more uncertainty in the size of heat shocks.

Concretely, we want to investigate if we also find increasing bond spreads, higher default risks, and lower debt levels in our panel regressions. Additionally, the empirical analysis further allows us to examine the heterogeneity suggested in Figures 4 and 5. The distribution of these shocks indicate that EM countries are more exposed to heat shocks, and our empirical analysis will provide a test of this hypothesis.

7.1 Empirical specification

Our identification strategy relies on our heat shock variable as an unexpected shock such that the heat shock is not confounded with unobserved determinants in the error term. We thus test the characterization of the heat shocks and the predictions of the sovereign default model by varying the dependent variable in the following regression setup:

$$\Delta Y_{i,t} = \alpha_i + \gamma_t + \beta heatshock_{i,t} + controls_{i,t} + \epsilon_{i,t} \tag{17}$$

Where $Y_{i,t}$ denotes the dependent variable. We show the results for the following dependent variables, (i) the first difference of the bond spread of country i in year t relative to US 10-year Treasuries, (ii) the first difference of debt-to-GDP, (iii) real GDP growth and

Table 7: Baseline regressions

VARIABLES	(1) Δ Bond Spreads	(2) Δ Bond Spreads	(3) Δ Bond Spreads	(4) Δ Bond Spreads	(5) Δ Bond Spreads
Heat Shock	0.6007**	1.0442**	0.9123**	0.8044**	0.3644
	(0.2408)	(0.4594)	(0.4302)	(0.3984)	(0.3208)
Precipitation			-0.0026	-0.0041	-0.0059
			(0.0075)	(0.0077)	(0.0050)
ND Readiness			0.0047	-0.0095	0.0263
			(0.0820)	(0.0085)	(0.0520)
Δ Ln(Reserves) × 100			-0.0139**	-0.0153**	-0.0152**
			(0.0068)	(0.0069)	(0.0063)
Terms-of-Trade			-0.0040	-0.0040	0.0151**
			(0.0081)	(0.0083)	(0.0075)
Inflation				0.1823**	0.0998*
				(0.0852)	(0.0574)
Real GDP Growth					-0.3702***
					(0.1305)
Debt-to-GDP					0.0057
					(0.0136)
Observations	893	893	893	893	893
R-squared	0.0046	0.1187	0.1317	0.1638	0.2600
Country FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes

Note: Full sample regressions using the pooled sample of EM's and AM's. Δ bond spread is the first difference in bond spreads. The heat shock variable is constructed as in equation 1, where μ is an expanding mean from 1901-1995. Controls include precipitation, ND Readiness Index, log first difference of reserves × 100, terms-of-trade, inflation, GDP growth and Debt-to-GDP. Clustered standard errors at the country level in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

(iv) the first difference of the Fitch sovereign credit rating.[7] $Heatshock_{i,t}$ is our heat shock variable defined in equation 1. We include country fixed effects α_i and year fixed effects γ_t. Following Cevik and Jalles (2022), the controls include real GDP growth, inflation, debt-to-GDP, the first difference of log international reserves, and the terms-of-trade. To capture climate-change adaptation we add the Notre Dame Readiness Index, and climate controls include precipitation. Standard errors are clustered at the country level and the data are at annual frequency.

7.1.1 Heat shocks direct and indirect effects

Table 7 reports estimates of equation 17, with the first difference of the bond spread as the dependent variable. To shed light on the channels through which heat shocks affect spreads, the table begins with a univariate specification and builds toward a fully saturated model with fixed effects and the complete set of controls.

[7]The Fitch rating we used is a 21 point numerical scale, where higher values indicate stronger creditworthiness

Column (1) of 7 reports the univariate regression. A one-standard-deviation increase in the heat shock variable raises bond spreads by 0.60 basis points. This magnitude can be expressed in degrees Celsius for the average country in the estimation sample. The average country exhibits a within-country long-run temperature standard deviation σ_i^{LR} of 0.45 °C, such that a one-standard-deviation anomaly corresponds to a deviation of roughly 0.45 °C from the country's temperature trend. Equivalently, the estimate implies an effect of approximately $0.60/0.45 \approx 1.3$ basis points per °C above the temperature trend. This column thus captures the total, unconditional effect of heat shocks on spreads.

Column (2) adds country and year fixed effects. The country effects absorb time-invariant heterogeneity, such as persistent differences in institutions or shallower financial markets, while the year effects absorb common global shocks such as a Federal Reserve tightening cycle or global business cycles.

By using fixed effects, we already account for some heterogeneity in our sample. The point-estimate increases to 1.04, meaning that a one standard deviation increase in temperatures above the trend increases bond spreads by approx. 1 basis points. Converted to degrees celsius we see that the direct effect of heat shocks is 2.32 basis points per °C increase above the trend when controlling for fixed effects.

Column (3) introduces a set of climate and macroeconomic controls. The point estimate remains roughly the same. This is important as we want to avoid any omitted variable bias. The only control that really makes a difference are the growth of annual reserves. A one-percentage-point increase in reserve growth is associated with a 0.0139 basis-point decline in the change in spreads, all else being equal. Faster reserve accumulation thus signals lower balance-of-payments and debt rollover risk. This in turn allows international financial markets to reduce the risk profile of countries even when hit by a heat shock, resulting in lower spreads.

Column (4) adds inflation. The direct effect of a heat shock is reduced to 0.80 and remains significant at the 5% level. Conditioning on inflation is important, since a growing literature shows that heat shocks could transmit to prices through a food-price channel (Mukherjee and Ouattara, 2021; De Winne and Peersman, 2021; Peersman, 2022). Inflation itself enters with the expected sign: a one percentage point increase in CPI inflation is associated with a 0.18 basis-point increase in the change in spreads, consistent with investors pricing the erosion of real returns. Please also note that the effect of inflation and heat shocks combined are roughly the same as the uncontrolled coefficient found in column (2). Inflation thus forms the first channel through which heat shocks impact bond spreads.

Column (5) further adds real GDP growth and debt-to-GDP as controls. The direct effect of heat shocks falls to 0.36 and is no longer statistically significant. Real GDP growth enters highly significant and with the expected sign, where higher growth is associated with lower spreads. Next to inflation, GDP growth and debt levels are the other channels through which heat shocks impact bond spreads. With only GDP growth and inflation being statistically significant.

When comparing the different channels, we can summarize that inflation takes about 20% of the total effect that heat shocks have on bond spreads. GDP growth accounts for about 33% of the effect and the remainder are the direct effects of heat shocks on bond spreads. This remainder captures the uncertainty channel previously discussed in the theoretical model. So almost half of the effect of heat shocks on bond spreads can be attributed to an increase in uncertainty.[8]

This result is consistent with the theoretical model. As a general equilibrium framework, the model also delivers predictions for debt levels and default probabilities, which we test in turn below, alongside the assumption regarding the heat shock damages imposed on the income process.

7.1.2 Debt, GDP growth and default risks

The theoretical framework showed that in equilibrium debt levels are lowered, as either sovereigns default on debt or sell fewer bonds as governments adjust for the higher risk-premium. Heat shocks in the theoretical model impact income only modestly as they are low mean shocks and temporary. However, this effect of heat shocks on income is imposed in the model. Testing this no impact assumption on GDP can strengthen our theoretical model. Lastly, default risks increase in our theoretical model. In our analysis we use credit ratings to capture default probabilities empirically.

To investigate this, we keep our previous specification 17, but use as dependent variables ΔDebt-to-GDP, Real GDP growth, and ΔFitch ratings respectively for each column of table 8. We keep the same controls as found in column (5) of table 7. For ease of comparison, column (5) of the previous table is copied to the first column, such that all the relevant empirical results on heat shocks appear in one table.[9]

The attentive reader will notice additional controls have been added to column (2) and (3). For the regression explaining ΔDebt-to-GDP we have added real GDP growth and lagged Debt-to-GDP to get the standard macroeconomic debt-dynamics equation. When explaining real GDP growth, we have added lagged real GDP to account for size, as is common in convergence theory.

As before, we focus on the uncertainty channel of heat shocks. We thus look at the direct effect of heat shocks and not the indirect effects going through inflation, debt accumulation or GDP. Column (2) shows that heat shocks clearly lower ΔDebt-to-GDP when heat shocks occur. A one °C increase in temperature above the expected trend lowers debt-to-GDP levels by 5.3 percentage points[10]. We confirm empirically that governments lower their

[8]There is a part of uncertainty that is also captured through the inflation channel, as food prices often have futures or options that also contain an uncertainty component.

[9]The theoretical counterparts of these variables can be found in table 6.

[10]We prefer to express our results in terms of degrees instead of standard deviations. To get results expressed in degrees Celsius, we divide the point estimates by the standard deviation of long-run temperatures found in our sample, see also equation 1.

Table 8: Regressions by sovereign default model outcomes

VARIABLES	(1) Δ Bond Spreads	(2) Δ Debt-to-GDP	(3) Real GDP Growth (pp)	(4) Δ Fitch Ratings
Heat Shock	0.3644	-2.3892*	-1.0683	-0.2694
	(0.3208)	(1.4269)	(0.9815)	(0.3156)
Post Paris × Heatshock				-0.6909*
				(0.3768)
Inflation	0.0998*	0.1155	-0.2450***	0.0071
	(0.0574)	(0.1474)	(0.0454)	(0.0257)
Debt-to-GDP	0.0057		-0.0382***	0.0011
	(0.0136)		(0.0109)	(0.0032)
Real GDP Growth	-0.3702***	-0.8280***		0.1640***
	(0.1305)	(0.1238)		(0.0197)
Debt-to-GDP Lag 1		-0.2557***		
		(0.0408)		
Ln(Real GDP) Lag 1			-0.0642***	
			(0.0090)	
Observations	893	893	893	755
R-squared	0.2600	0.2864	0.6076	0.4776
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: Full sample regressions using the pooled sample of EM's and AM's. Δ Bond Spread is the first difference in bond spreads. Δ Debt-to-GDP is the first difference in Debt-to-GDP. Post Paris is a year dummy which turns 1 starting from the year 2015. Controls include first lagged difference of Debt-to-GDP in levels, precipitation, ND Readiness Index, log first difference of reserves, terms-of-trade, inflation and GDP growth. Real GDP growth is GDP growth in percentage points. Controls include first lag of $\ln(GDP_{levels})$, precipitation, ND Readiness Index, log first difference of reserves, terms-of-trade, inflation and Debt-to-GDP. Δ Fitch Ratings is the first difference of the Fitch credit ratings that are converted to a 21 numerical scale. Higher values indicate stronger creditworthiness of the country. Controls include precipitation, ND Readiness Index, log first difference of reserves, terms-of-trade, inflation, GDP growth and Debt-to-GDP. The heat shock variable is constructed as in equation 1, where μ is an expanding mean from 1901-1995. Clustered standard errors at the country level in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

debt levels after being hit by a heat shock. A caveat is that our debt-accumulation equation gives some mixed signals. The signs and size of the impact of real GDP growth is as expected ex-ante. The sign of the lagged debt-to-GDP coefficient is puzzling as it runs counter to theory.

Column (3) on the other hand follows the full logic of conventional macroeconomic growth theory. Debt lowers growth as can be seen by the negative coefficient. Looking at lagged real GDP we find a coefficient of -0.064 which is highly significant. Both the sign and the size of this convergence speed fully align with existing literature. Now focusing on heat shocks, we see that no significant effect is found, which indicates that at least heat shocks have no permanent effects on real GDP growth. This result directly confirms the assumption that was made in the theoretical model. We do see that an indirect effect of heat shocks on growth can occur via inflation. This is to be expected, as uncertainty can affect future prices, especially on agricultural products. This result hints at how heat shocks could affect outcomes and is investigated further in this paper.

Lastly, column (4) gives us the results for default probabilities. To proxy for default risk, we use credit ratings from Fitch Ratings. Higher Fitch rating scores correspond to lower default probabilities. Again we find macroeconomic results expected from theory: growing economies tend to have lower default risks. More importantly is that at first glance we see no direct impact of heat shocks on default risk.

Once we account for the Paris Agreement, via an interaction term, heat shocks become relevant. For post Paris Agreement periods we see that credit agencies have started to incorporate heat shocks as possible credit default risks. Our research thus confirms and expands the work of Cappiello et al. (2023). From the Paris agreement onwards, a one °C increase in temperature above the expected trend, lowers Fitch ratings by 1.5 point on their 21 risk score. This finding is consistent with the literature (Bolton and Kacperczyk, 2021; Degryse et al., 2023; Ilhan et al., 2021).

The results shown up till here indicate that more heterogeneity is present. Column (4) indicates a speeding up of events since the Paris Agreement. Looking back at heat shock distribution in Figures 4 and 5. We see that only EM have higher uncertainty in the last two decades, whilst AM remain stable. A split-up of our sample in AM and EM might offer more insights.

7.2 Heterogeneity

To examine the hidden heterogeneity we re-estimate equation 17 for EM and AM subsamples.[11] Previously in table 7 column (5) we found that the direct uncertainty channel was not significant if we take the whole sample into account.[12]

[11] Table 13 in the Appendix gives the country list of each subsample.

[12] Pro memorie: the uncertainty channel is the direct effect of heat shocks that does not go via inflation, GDP growth or debt.

Table 9: EM AM Sub-Sample Results

	(1)	(2)	(3)	(4)
VARIABLES	Δ Bond Spread	Δ Bond Spread	Δ CDS Spread	Δ CDS Spread
SAMPLE	EM	AM	EM	AM
Heat Shock	0.7667**	0.4776	1.8354*	0.8039
	(0.3768)	(1.0872)	(1.1005)	(1.0564)
Observations	512	381	249	127
R-squared	0.4202	0.3909	0.3736	0.2803
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: Subsample regressions using EM's and AM's sub-sample. Δ bond spread is the first difference in bond spreads. Δ CDS spread is the first difference of the country's credit default swap spreads. The heat shock variable is constructed as in equation 1, where μ is an expanding mean from 1901-1995. Controls include precipitation, Notre Dame Readiness Index, log first difference of reserves, terms-of-trade, inflation, GDP growth and Debt-to-GDP. Clustered standard errors at the country level in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

When examining column (1) and (2) from Table 9, we see the masked heterogeneity mentioned before. The direct uncertainty effect is only significant for EM, whilst the AM remains insignificant. The results show that a one-standard-deviation increase in the heat shock variable widens bond spreads by 0.77 basis points. Or put differently, a one °C increase in temperature above the expected trend increases spreads by 1.44 basis points for EM and is not significant for AM.

This is almost double the effect found when looking at the whole sample. It is a clear indication that these heat shocks are distributed unevenly and only worsen financial conditions for emerging markets. The results are in line with the theoretical model, yet more support for the uncertainty channel is desirable.

To strengthen our argument we add CDS spreads as dependent variable. We once again compare AM and EM to see if our results survive. CDS spreads better capture the risk of defaults. Bond spreads capture a broader spectrum of effects such as e.g. liquidity risk, while CDS focus more on pricing in uncertainty risk arising from default as the pay-offs of these financial derivatives are directly tied to default events. Comparing CDS and bond spreads gives us insights of whether heat shocks operate more via risk premia, or whether it is more a liquidity access concern.

Focusing in on column (3) and (4) we see the same overall pattern occur. This strengthens our findings and indicates that indeed heat shocks are distributed differently between EM and AM. Only EM exhibit wider spreads as a result from heat shocks.

We can also compare column (3) to (1) and we observe that CDS spreads respond almost twice as strongly as bond spreads. This is a clear indication that heat shocks operate through default risks and risk premia and are less associated with e.g. liquidity constraints. If that were the case we would expect a small and non-significant effect on CDS spreads.

To come full circle, Table 9 indicates that the main channel identified in the theoretical model holds empirically. Heat shocks represent an uncertainty risk for sovereigns in EM, and as a result financial markets price in this risk by raising the risk premium. Higher spreads in turn worsen financial conditions for EM, prompting them to lower their debt to more sustainable levels. By contrast, AM countries face lower temperature variability, and accordingly we find no significant bond market response following a heat shock.

The geographic difference explains why EM are more exposed, but we ask whether economic and policy-driven choices can further explain the effect of heat shocks in emerging markets.

7.2.1 Linking agriculture to heat shocks

In a final set of regressions, we investigate why EM countries exhibit wider bond spreads following heat shocks. We hypothesize that countries with large agricultural shares of GDP are more vulnerable to heat shocks. This hypothesis is supported by studies such as Jägermeyr et al. (2021), who document that temperature increases reduce agricultural output in the absence of perfect adaptation.

This adaptation framework is central to our argument: the rising uncertainty of heat shocks means that the agricultural sector cannot adapt perfectly to changing temperatures. To test this hypothesis, we estimate the following regression:

$$\begin{aligned}\Delta spread_{i,t} = \alpha_i + \gamma_t + heatshock_{i,t} + agriculture_{i,t} \\ + heatshock_{i,t} \times agriculture_{i,t} + controls_{i,t} + \epsilon_{i,t}\end{aligned} \tag{18}$$

where $\Delta spread_{i,t}$ denotes the first difference of the bond spread for country i at time t, $heatshock_{i,t}$ denotes the heat shock variable as defined in equation 1, and $agriculture_{i,t}$ is the share of agricultural output relative to GDP. We include country and year fixed effects. Controls comprise precipitation, the ND Readiness Index, the log first difference of reserves scaled by 100, terms of trade, inflation, GDP growth, and the debt-to-GDP ratio. Standard errors are clustered at the country level. Table 10 presents the results.

As before, we focus on the uncertainty channel of heat shocks. We thus look at the direct effect of heat shocks in EM and not the indirect effects going through inflation, debt accumulation or GDP growth. Column (1) of Table 10 is copied over from column (1) of Table 9. Column (2) adds an interaction between the heat shock variable and agricultural output as a share of GDP.

Table 10: Countries most vulnerable to heat shocks

VARIABLES	(1) Δ Bond Spread	(2) Δ Bond Spread
SAMPLE	EM	EM
Heat Shock	0.7667**	-1.9043
	(0.3768)	(1.3062)
Heat Shock × Agri Output - to - GDP		0.2234*
		(0.1323)
Observations	512	512
R-squared	0.4202	0.3120
Controls	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes

Note: EM sample regressions using Δ bond spread defined as the first difference in bond spreads as dependent variable. The heat shock variable is constructed as in equation 1, where μ is an expanding mean from 1901-1995. Agriculture Output - to - GDP is the share of agricultural output scaled by GDP. Controls include precipitation, ND Readiness Index, log first difference of reserves, terms-of-trade, inflation, GDP growth and Debt-to-GDP. Clustered standard errors at the country level in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

Comparing column (2) with (1) we see that heat shocks' direct effect becomes insignificant. This tells us that there is no remaining uncertainty effect left when we account for agriculture. Column (2) provides evidence that heat shocks increase risk premia in EM countries that are heavily dependent on agriculture. For each percentage point increase in agricultural share of GDP, we expect that a one °C increase in temperature above the expected trend increases bond spreads by 0.42 basis points. So in other words an EM country will have an additional 0.42 basis points spread per additional % share of GDP spent on agriculture.

When also looking at the new point estimate for heat shocks, we can calculate that heat shocks start to increase spreads when agriculture share exceed more than 8.5% of GDP. Our EM sample has an average agricultural share of 11%, this translates to an average expected effect of approximately 1 basis point increase in spreads per one °C increase in temperature above the expected trend. The highest share in our sample corresponds to 31% agricultural share of GDP. In turn, a heat shock of one °C would result in an increase of 9.45 basis points in bond spread for that country.

The importance of agriculture should not be underestimated. The Least Developed Countries (LDCs) tend to experience frequent heat anomalies and rely heavily on agriculture, which can account for up to 50% of their total output. These countries already have poor access to international financial markets, and our results indicate that their high agricultural shares will force them to pay steep risk premia for that access.

8 Conclusion

This paper studies the effects of heat shocks on sovereign debt markets by combining a quantitative sovereign default model with panel data econometrics. A key contribution of our analysis is to contrast two types of disaster risk: the high-mean, low-uncertainty disaster shocks emphasized in the existing literature (Mallucci, 2022) versus the low-mean, high-uncertainty shocks that characterize heat shocks (Weitzman, 2011; Callahan and Mankin, 2022). We demonstrate that uncertainty is an important driver in financial and macroeconomic outcomes.

In our calibrated model, we show that uncertainty has real impact, even when expected damages are small. By using counterfactual analysis we determine that uncertainty caused by heat shocks widen sovereign bond spreads by 66 basis points, increase the probability of default by 2.1%-points, and lower debt-to-GDP levels by 5%-points. Lower debt is a consequence of higher spreads and the need of governments to reach more sustainable levels of debt. The theoretical model thus gives first indications that uncertainty itself emerges as a transmission channel through which climate change adversely affects sovereign borrowing.

This uncertainty channel is then put to the test empirically in our panel of 76 countries spanning 1995–2017. We first construct a heat shock variable and show that the heat shock densities for emerging markets exhibit fatter tails compared to those for advanced markets. Fatter tails indicate that emerging markets face greater uncertainty in heat shock effects. This is a first descriptive hint at heterogeneity in the data.

In a univariate regression, a one-standard-deviation increase in the heat shock variable widens bond spreads by 0.60 basis points. We translate our results in a more intuitive per °C terms. For each °C above the expected temperature trend, we see that bond spreads increase by 1.3 basis points. We however noted some heterogeneity in the distribution of heat shocks. This uneven distribution lead us to employ country and year fixed effects alongside climate and macroeconomic controls: the coefficient rises to approximately 2.08 basis points per °C above the trend and remains significant at the 5% level.

Inspired by our theoretical framework and existing literature on heat shocks, we find that inflation is an important channel through which uncertainty impacts bond spreads. Up to this point we still treat advanced and emerging markets in the same fashion. When we split the sample into emerging and advanced markets, the heat shock coefficient is significant for the EM subsample but statistically indistinguishable from zero for advanced markets.

CDS spreads corroborate this pattern, indicating that the widening carries a credit risk component. This heterogeneity is consistent with the mechanism of the sovereign default model: EM countries face greater variability in the heat shock variable, and bond markets price in this additional uncertainty by imposing a risk premium on sovereign debt. The model predicts that varying uncertainty while holding mean income damages constant is sufficient to generate variation in bond spreads, and the EM-AM contrast in the data

provides empirical support for this transmission mechanism. The adverse effects on bond spreads are stronger for countries with larger shares of agricultural output relative to GDP, identifying agriculture as an important explanation why heat shocks increase sovereign risk. Countries that diversify their economies away from agriculture are more resistant to the effects of heat shocks.

The paper carries clear policy implications. While advanced markets have contributed the bulk of historical CO_2-equivalent emissions, it is emerging markets that face higher borrowing costs through fatter-tailed heat shock densities. This externality could be mitigated by stronger international climate finance mechanisms, including concessional lending and multilateral guarantees, to prevent uncertainty-driven risk premia from depressing investment in mitigation and adaptation. The role of uncertainty in sovereign bond markets also underscores the importance of building ex-ante fiscal buffers to self-insure against shocks. Advanced markets and multilateral institutions can play a role by facilitating technical assistance such that vulnerable countries are less exposed to the financial market consequences of heat shocks. It is also reasonable to expect that the adverse effects of heat shocks are an order of magnitude larger for low-income countries that lack access to international sovereign bond markets, reinforcing the urgency of these policy responses.

To conclude, our findings show that climate change transmits through sovereign debt markets not only via expected damages, but also through uncertainty. Low mean, but high uncertainty events such as heat shocks impose meaningful costs on sovereigns by tightening financing conditions.

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9 Appendix

9.1 Additional Summary Statistics

Table 11: Summary Statistics - EM Sample

Variable	Obs	Mean	Std. Dev.	Min	Max	Source
Δ Bond Spreads	249	-0.128	2.540	-16.012	14.359	Bloomberg
Δ CDS Spreads	249	0.052	2.230	-13.069	16.032	Bloomberg
Heat Shock	249	0.362	0.401	-0.177	1.948	CRU
Heat Shock Truncated	249	0.364	0.399	0.000	1.948	CRU
Precipitation	249	93.436	62.455	0.936	281.270	CRU
Δ Fitch Credit Ratings	216	-0.782	1.467	-4.000	2.000	Fitch
Δ Ln(Reserves)	249	-0.006	0.229	-1.672	1.096	IMF
Inflation CPI	249	6.112	5.725	-0.418	25.000	IMF
Debt-to-GDP	249	51.636	19.932	14.976	111.660	IMF
Δ Debt-to-GDP	249	2.825	10.572	-12.349	31.440	IMF
ND Readiness Index	249	41.018	10.789	18.757	69.245	ND-Gain
Terms-of-Trade	249	118.225	31.869	74.611	264.204	WDI
Real GDP Growth	249	3.404	3.599	-11.991	16.048	WDI
Ln(GDP constant prices)	249	5.338	1.327	2.878	9.326	WDI
Agriculture Output-to-GDP	249	11.397	5.998	2.108	30.993	WDI

Note: Spread changes are the annual first difference in spreads. The heat shock variable is constructed as in equation 1 and is computed as the deviation of annual temperature with the long run temperature (expanding window 1901-1995) scaled by the long run standard deviation of temperature (expanding window 1901-1995). Precipitation is defined as annual precipitation in millimeters. ND Readiness Index is the Notre Dame Readiness Index. Δ ln(reserves) is the log first difference of foreign currency reserves over GDP, where non-domestic currency is converted to the USD. Δ Fitch Credit Ratings is the annual first difference of the country's Fitch credit rating, where the rating is converted to a 21 points scale. Higher values indicate stronger creditworthiness. Agriculture Output-to-GDP is the share of agriculture in the GDP. GDP growth, CPI Inflation, Debt-to-GDP, Budget Balances and Terms-of-Trade are winsorized at the 5% level.

Table 12: Summary Statistics - AM Sample

Variable	Obs	Mean	Std. Dev.	Min	Max	Source
Δ Bond Spreads	127	-0.235	1.059	-4.870	5.288	Bloomberg
Δ CDS Spreads	127	0.003	0.941	-4.119	6.095	Bloomberg
Heat Shock	127	0.148	0.107	-0.161	0.368	CRU
Heat Shock Truncated	127	0.156	0.092	0.000	0.368	CRU
Precipitation	127	76.053	24.570	37.247	144.593	CRU
Δ Fitch Credit Ratings	127	-0.244	0.879	-6.000	1.000	Fitch
Δ Ln(Reserves)	127	0.037	0.145	-0.256	0.428	IMF
Inflation CPI	127	1.433	1.159	-0.418	4.464	IMF
Debt-to-GDP	127	76.892	33.052	24.976	150.646	IMF
Δ Debt-to-GDP	127	3.102	10.277	-12.349	31.440	IMF
ND Readiness Index	127	64.511	13.575	19.103	80.192	ND-Gain
Terms-of-Trade	127	99.776	9.558	74.453	152.926	WDI
Real GDP Growth	127	1.354	2.697	-8.631	17.048	WDI
Ln(GDP constant prices)	127	6.623	0.949	5.119	8.270	WDI
Agriculture Output-to-GDP	127	1.769	1.055	0.579	7.034	WDI

Note: Spread changes are the annual first difference in spreads. The heat shock variable is constructed as in equation 1 and is computed as the deviation of annual temperature with the long run temperature (expanding window 1901-1995) scaled by the long run standard deviation of temperature (expanding window 1901-1995). Precipitation is defined as annual precipitation in millimeters. ND Readiness Index is the Notre Dame Readiness Index. Δ ln(reserves) is the log first difference of foreign currency reserves over GDP, where non-domestic currency is converted to the USD. Δ Fitch Credit Ratings is the annual first difference of the country's Fitch credit rating, where the rating is converted to a 21 points scale. Higher values indicate stronger creditworthiness. Agriculture Output-to-GDP is the share of agriculture in the GDP. GDP growth, CPI Inflation, Debt-to-GDP, Budget Balances and Terms-of-Trade are winsorized at the 5% level.

Table 13: List of EM and AM countries

Country Name	Income Category	Country Name	Income Category
Angola	EM	Malaysia	EM
Argentina	EM	Malta	AM
Australia	AM	Mexico	EM
Austria	AM	Morocco	EM
Azerbaijan	EM	Mozambique	EM
Belarus	EM	Netherlands	AM
Belgium	AM	New Zealand	AM
Bolivia	EM	Nigeria	EM
Brazil	EM	Norway	AM
Canada	AM	Pakistan	EM
Chile	EM	Peru	EM
China	EM	Philippines	EM
Colombia	EM	Poland	EM
Croatia	EM	Portugal	AM
Cyprus	AM	Romania	EM
Czech Republic	AM	Russia	EM
Côte d'Ivoire	EM	Senegal	EM
Denmark	AM	Slovak Republic	AM
Dominican Republic	EM	Slovak Republic	EM
Ecuador	EM	Slovenia	AM
Egypt	EM	South Africa	EM
Ethiopia	EM	Spain	AM
Finland	AM	Sri Lanka	EM
France	AM	Sweden	AM
Germany	AM	Turkey	EM
Ghana	EM	Ukraine	EM
Greece	AM	United Kingdom	AM
Honduras	EM	Uruguay	EM
Hungary	EM	Venezuela	EM
Iceland	AM	Vietnam	EM
India	EM	Zambia	EM
Indonesia	EM		
Ireland	AM		
Israel	AM		
Italy	AM		
Kazakhstan	EM		
Kenya	EM		
Korea	AM		
Latvia	AM		
Lithuania	AM		
Lithuania	EM		

Note: the country classification are obtained from the IMF World Economic Outlook database.

9.2 Additional Figures

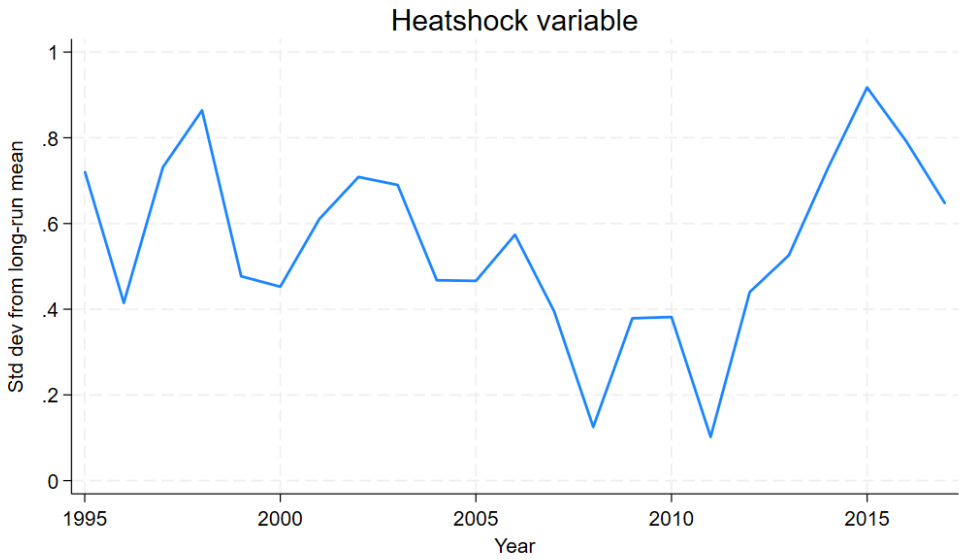


Figure 8: Non-parametric regression of the heat shock variable in equation 1 over time for the Dominican Republic

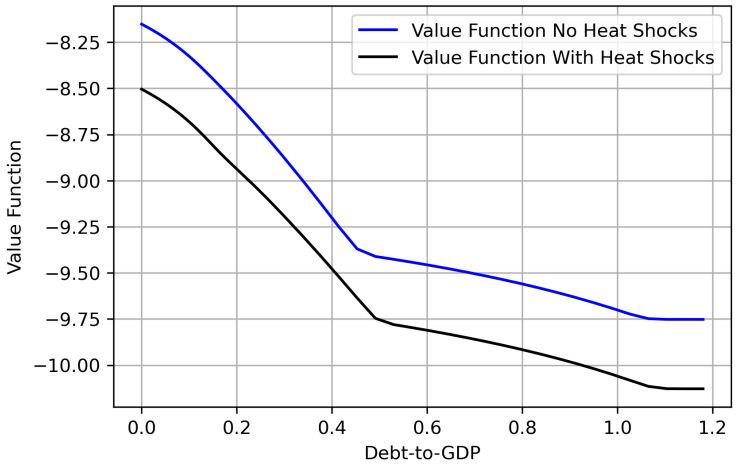


Figure 9: Value Function simulating the economy of the Dominican Republic

9.3 Equilibrium

In equilibrium, the government sets the policy for default, repayment, issuance or purchase of bonds in order to maximize the welfare of the representative household, subject to the budget constraint of the small open economy and to the constraint implied by the international financial market's pricing of debt. The equilibrium is defined as:

Definition 1

A recursive equilibrium in the small open economy is characterized by

- *a set of value functions for the representative household V, V^{nd}, and V^{d}*
- *government policies for default d and asset holdings b'*
- *a government debt price function q*

such that

- *the debt price function is consistent with optimization by foreign lenders 16*
- *given the debt price function q, the value functions of the household and the policy functions of the government solve the maximization problem 9, 11, 13, 14*
- *the resource constraint of the small open economy is satisfied*