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Looking beyond Traditional Drivers: Climate Effects on Eurozone Sovereign Yields

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Abstract: In the present study we examine the relationship among sovereign yields, temperature and precipitation using a large monthly panel data set which consists of 20 eurozone members, over the period 1980M1 – 2023M4. To account for possible asymmetries along the distribution of the climate variables we assume a quadratic modelling specification and apply various mean panel estimation techniques of heterogeneous coefficients. At a next step, to consider possible nonlinearities in the distribution of the dependent variable (sovereign yields), we apply the quantile via moments methodology of Machado and Santos Silva (2019), which accounts for possible cross-sectional dependence and slope heterogeneity. We contribute to the existing literature in two main ways. First, by applying a quantile methodology that provides a more in-depth analysis of the climate effects along the distribution of the sovereign yields, especially in the presence of non-normally distributed data. Second, we find that climate change, as proxied by higher temperatures or lower precipitation (drought), will increase the sovereign risk of all countries, but the magnitude of the impact will be higher for countries that are already characterized by higher sovereign risk levels and/or face extreme weather conditions (hotter countries and/or countries with low levels of precipitation).

Keywords: climate change; panel quantile regression; slope heterogeneity; asymmetries; sovereign yields; temperature; precipitation

JEL Classification: C23; G15; H63; Q51; Q54

1. Introduction

While some may still find the impact of anthropogenic climate change irrelevant or insignificant, most recognize its effects, which sadly are becoming both more frequent and more intense. The effects of climate change are far reaching but, in many cases, because their impact may not always be immediate, they tend to be clouded by significant uncertainty. Economic activity and as such economic policy are certainly impacted by climate change in numerous ways. In this paper we explore how two climate related variables, namely temperature and precipitation, can affect sovereign risk as measured by yields on sovereign bonds.

We contribute to the existing literature in two ways. First, by applying a quantile methodology, assuming a quadratic modelling specification, that accounts both for cross – sectional dependence and slope heterogeneity. This method allows for a more in-depth analysis of the climate effects along the distribution of the sovereign yields, especially in the presence of non-normally distributed data. Second, by finding evidence that climate change will increase the sovereign risk of all countries, but the magnitude of the impact will be higher for the countries that are already characterized by a higher sovereign risk level and/or face extreme weather conditions (hotter countries and/or countries with low levels of precipitation). The main findings of our research are the following: First, we find strong evidence of a dual non-linear relationship between the variables under study. As a results, the mean panel estimators cannot fully identify the relationship between precipitation and sovereign yields due to limitations arising from their mean approach properties. Second, we find that the impact of temperature on sovereign yields increases in magnitude as the sovereign risk rises and/or as the temperature rises. Additionally, the impact of precipitation on sovereign yields increases in magnitude as the sovereign risk rises and/or the precipitation decreases.

The rest of the paper is organized as follows: in Section 2 we discuss the relevant literature on the relationship between climate related variables and sovereign risk. Section 3 describes the data and the statistical properties of the variables used, along with the econometric methodology. In Section 4 we present and discuss the empirical results and several robustness checks. Section 5 concludes and discusses possible directions for future research.

2. Literature Review

The literature studying the impact of climate related risk on the fiscal sector is relatively small but growing. There are two main lines of research and relevant hypotheses: 1) how do climate and weather variables affect sovereign risk or sovereign default, and 2) how do climate related and weather events affect the fiscal budget. An alternative classification of the relevant literature could be in terms of transition and physical risks. Transition risks refer to those associated with adjusting to a low-carbon economy, while physical risks are those emanating from adverse weather events.

In one of the first papers focusing on the impact of extreme weather events on budget balances in a panel of countries, Lis and Nickel (2010) find that the change in the budget balance as a percent of GDP following an extreme weather event is relatively modest at 0.23%. However, the impact increases up to 0.47% when they focus on the developing economies in their sample of 138 countries in total. Moreover, they find that for warmer countries, which tend to be more vulnerable to extreme weather events, the fiscal impact is larger. The authors use panel fixed effects, instrumental variables fixed effects, and GMM estimation in a panel of 138 countries over the period from 1985 to 2007, with the change in the budget balance as a dependent variable and different definitions of extreme weather events as the independent, while controlling for a set of macroeconomic, budgetary and political variables.

Melecky and Raddatz (2011) use a panel vector autoregression model to analyze the impact of three different types of disaster shocks on government expenditures, revenues, and deficits. More specifically, using annual data from 1975 to 2008 on high- and middle-income countries, the authors find that the three types of disaster shocks, namely geological, climatic and other disasters, have a negative impact on both output and deficit levels by leading to higher expenditures and lower revenues. This effect is greater for the lower-middle income countries of their sample. Interestingly, they also find that higher debt levels (associated with deficit deteriorations) signal better ability to borrow in capital markets rather than a constrained fiscal position. The authors also show that countries with stronger financial or insurance markets are able to better cope with the negative impacts on output from disaster shocks, although in different ways. These qualitative differences are worth exploring further as they have important policy implications.

Crifo et. al. (2017) find that environment, social and governance (ESG) indicators are important in explaining sovereign credit risk. Specifically, using data on 23 OECD countries over the period from 2007 to 2012 and employing a panel IV methodology with country and time fixed effects, they show that a higher ESG rating has a negative effect on sovereign bond spreads. However, the effect of these extra-financial metrics while significant, is not as important as credit ratings.

Kling et. al. (2018) use a panel ordinary least squares model linking sovereign bonds yields to measures of climate vulnerability and social preparedness, while controlling for standard macroeconomic variables. Using data for countries on the V 20 group of climate vulnerable countries the authors find evidence of a significant positive impact of climate vulnerability measures, such as dependency on natural capital or water dependency, on sovereign borrowing costs. Social preparedness on the other hand is associated with a negative impact on sovereign yields. Additionally, using a logistic model, they find evidence of a negative correlation between climate vulnerability and access to capital markets.

Bachner and Bednar-Friedl (2019) develop a computable general equilibrium model for Austria to analyze the impact of climate change on public budgets. The authors consider three climate scenarios with a model base year of 2008 and trace the impact in ten sectors of the economy for a 2 Celsius increase in temperature by 2050. They show that the overall effect of climate change on GDP, welfare, and budgets is negative. Moreover, as climate change related events are likely to require additional government aid, other publicly provided services are impacted negatively. When considering counterbalancing instruments and policies, they identify different channels with which climate change impacts affect public budgets. Higher capital taxes and cuts in transfers reduce welfare losses, while an increase in labor and output taxes has the opposite effect. Additionally, an increase in foreign borrowing reduces welfare losses more so than employing domestic counterbalancing policies, but at the expense of higher deficit and debt.

One of the first papers to study the effect of climate change on sovereign credit ratings is that of Cevik and Jalles (2020). Using a sample of 67 advanced and developing economies over the period from 1995 to 2017 and three estimation methodologies (OLS, binary-choice model, and 2SLS with instrumental variables), they examine the relationship between climate vulnerability and climate resilience on credit ratings, controlling for standard macroeconomic and fiscal variables. Their results based on the whole sample indicate that on average a 1% increase in climate vulnerability lead to a 0.23% drop in credit worthiness, while an increase of 1% in climate resilience leads to a 0.09% in credit rating. An important part of their analysis is then done by splitting the sample between advanced and developing economies. In line with other studies, the effects mentioned above are different in the two groups. More specifically, in advanced countries the effect of climate change vulnerability becomes insignificant, while in developing countries the effect is amplified. Climate change resilience is significant in both groups but the effect is again much larger for developing countries. Clearly, as the authors point out, these differences have significant implications for policy both at the national but also supranational levels. It will also be interesting to examine who and if this pattern changes as more countries may become climate vulnerable.

Beirne et. al. (2021a) study the effects of climate related risks on the pricing of sovereign bonds in a panel of 40 advanced and emerging economies using quarterly data from 2002 to 2008. Their findings indicate that both the immediate impact of climate risks (climate vulnerability) and resilience to climate risk have an important effect on the cost of foreign borrowing. They find the former to be more important than the latter. This affects disproportionally emerging economies many of which are more vulnerable to climate risks and may thus face a double challenge.

Focusing on six Southeast Asian economies which are more prone to climate stress, Beirne et. al. (2021b) estimate the links between climate vulnerability and resilience and sovereign bond yields. They use monthly data over the period from 2002 to 2018 and take two estimation approaches: country specific OLS regressions and a fixed effects panel model. Both approaches lead to the same main conclusion, namely that climate vulnerability has a significant positive impact on sovereign bond yields, while climate resilience has a negative but smaller effect. Reinforcing their results of their previous work stated above, the authors also point out how a vicious cycle can manifest in countries that face a higher climate risk. Higher sovereign yields increase the cost of borrowing needed to finance adaptation and resilience investment and a worsening of public finances.

A slightly different in focus but still related work is developed by Kling et. al. (2021) who focus on the impact of climate vulnerability on cost of debt and equity financing for private firms, as well as access to capital. The authors develop panel regressions and structural equations models with firm level data on 15,265 firms in 71 countries over the period from 1997 to 2017 and different measures of climate vulnerability based on the ND-GAIN index. They find that while climate vulnerability increases the cost of debt, the effect is insignificant for the cost of equity. The effect of the former also has an indirect effect through a negative impact on access to financing. This work to again emphasizes the uneven effects that countries who are more climate vulnerable will face despite the fact that they have not contributed by as much to climate change. This is an important point the authors make and deserves attention at the policy level, especially as climate policy should focus more on international cooperation.

Kizys et. al. (2021) further provide evidence of a positive relationship between temperature and sovereign bond yields. Using daily observations on 31 countries over the period from 1980 to 2020

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and different maturities, the authors use panel regressions and find that on average a 10°F increase in temperature leads to a 0.22 to 0.85 basis points increase in yields. Moreover, the also provide evidence of a non-linear, and more specifically quadratic, relationship between temperatures and bond returns.

Semet et. al. (2021) examine the relationship between sovereign bond spreads and ESG indicators. The authors identify 21 ESG metrics from a long list of relevant variables as the ones having the greatest impact on sovereign bond spreads. Their analysis covers the period from 2015 to 2020 and is based on 67 countries. Their results indicate that the environmental pillar is the most important one, followed by the governance and lastly the social pillar when looking at the whole sample. However, when looking at high vs. middle income groups, the transition risk is greater in the former group whereas the physical risk is greater in the latter. Finally, using a logit model they examine whether ESG indicators can predict a country's credit rating, and find that the environmental is not significant.

Boehm (2022) constructs a measure of temperature anomalies, i.e. deviations from average temperatures, using monthly data on 54 emerging economies over the period from 1994 to 2018. He then examines the relationship between sovereign creditworthiness and temperature anomalies and precipitation. His findings, using OLS panel regressions, indicate that higher temperature anomalies lead to increases in sovereign risk in countries that are either warmer and/or lag with respect to different measures on institutional development. Finally, the author highlights the importance of a recurring pattern, namely that countries such as the ones in this sample (i.e. emerging economies) stand to experience more negative impacts of climate change (proxied by increases in temperature anomalies in this paper), even though they have not contributed the same to global CO^2 emissions as more advanced economies. Therefore, in terms of policy recommendations, the focus should be on strengthening institutions and improving climate resilience by investing in adaptation strategies.

Building on their previous work[1] Cevik and Jalles (2022a) use a sample of 98 advanced and developing countries over the period from 1997 to 2017 to re-examine the relationship between sovereign bond yields and spreads and the ND-GAIN measures of climate vulnerability and resilience. The authors confirm their previous findings showing climate vulnerability as having a positive impact on both yields and spreads, whereas climate resilience has a negative one. Once again, this study also finds that the effects are greater in developing countries.

Cevik and Jalles (2022b) are perhaps the first to examine the relationship between climate change and sovereign defaults. The authors use a panel of 116 countries over the period from 1995 to 2017 and estimate the probability of sovereign default based as a function of climate vulnerability and resilience. Using a logit model in their baseline specification, they provide evidence of a strong positive impact of climate vulnerability of the probability of default, while climate resilience has a negative one. As in most previous studies, this one also finds evidence of differences among high and low-income counties, with the impact of the latter group being greater.

Assab (2023) studies how the urban heat island (UHI) effect and the urban forest cover can affect sovereign yields. The UHI effect refers to the higher land temperatures in urban areas as opposed to rural ones, as a result of human activity. The analysis is done for 68 countries over the period from 2008 to 2020. The author provides evidence of a negative impact of UHI on sovereign yields, which can be mitigated by the positive impact of urban forest. Moreover, the positive impact of urban forest cover is greater in countries with higher fiscal decentralization. The latter implies the importance of local policies when it comes to adaptation strategies. The impact of the UHI effect as well as of the urban forest cover deem more attention from researchers and should be further explored.

Cheng et. al. (2023) center their analysis on transition risks and examine whether these are reflected into the pricing of sovereign bond yields, as well as whether policies that address these risks can have a mitigating effect on sovereign bond pricing. The authors estimate a panel model with country and time fixed effects where sovereign yields are a function of a constructed measure of transition risks and a set of macroeconomic and fiscal control variables. Their results, based on a

[1] See Cevik and Jalles (2020) discussed above

sample of 25 countries during the period from 1995 to 2018, indicate that there is a positive relationship between transition risks and sovereign bond yields, while policies aimed to address such risks can have a negative effect.

Along the same lines, Collender et. al. (2023) also focus on transition risks and how these impact sovereign yields and spreads. Their sample includes 39 countries over the period from 1999 to 2021. The authors break down transition risks into three main components: CO^2 emissions, natural resources rents, and renewable energy consumption. These together with a set of macroeconomic control variables are used to explain sovereign yields and spreads in a panel setting over both the entire sample but also in two country groups (advanced and developing economies). Their results show a positive relationship between CO^2 emissions and borrowing costs in both country groups. The impact of natural resources rents and renewable energy consumption is however different among the two groups. While lower natural resources rents are associated with lower borrowing costs in advanced economies, the relationship is reversed for developing ones. As for renewable energy consumption, the link is indirect for advanced economies but again reverses for developing ones.

Klusak et. al. (2023) use machine learning to simulate the impact of climate change, as proxied by rising temperatures due to higher CO^2 emissions, to sovereign credit ratings. Their analysis, based on 109 countries, results in sovereign credit ratings that internalize the impact of climate change. These climate- adjusted ratings lead to substantial credit downgrades as early as 2030. However, if countries follow the Paris Climate Agreement and commit to following policies consistent with the 2°C target of temperature increases, the impact can be substantially reduced and even eliminated. The authors also quantify the monetary impact of downgrades driven by climate change for both the sovereign and corporate debt. Under a scenario consistent with stricter climate policies the additional borrowing cost for sovereign debt is estimated to be from US$45 to $64 billion, whereas it rises to US$105 to $203 billion under a "business as usual" scenario. Similarly, for corporate debt the above ranges are US$10 to $17 and US$35 to $61 billion under the two scenarios. As the authors point out, the model should be extended to include political instability due to climate change, transition, and litigation risks.

An interesting question examined in Saxena and Singh (2023) is whether markets reward countries whose governments participate in climate agreements. To answer this, the authors examine the relationship between sovereign yields before and after participation in climate agreements using a difference-in-differences approach. Focusing on the Kyoto Protocol and the Paris Agreement, they find that investors indeed favor governments that participated in these agreements, with the effect being stronger in the case of the Kyoto Protocol. The role of incentives, which may be the reason why these effects are different, is an open question which the authors emphasize.

Sun et. al. (2023) revisit the relationship between climate risks and sovereign ratings. The authors employ a generalized logit ordered model with climate vulnerability and readiness as the two main explanatory variables, together with standard macroeconomic variables shown to affect sovereign ratings. In addition, a random forest model is used to compare the importance of the two climate variables relative to the other indicators. In line with previous study, their results show that climate vulnerability has a significant negative effect on sovereign ratings, while climate readiness a positive one. Both impacts are found to be higher for developing and high-damage countries.

Overall, the above literature review revealed that there is a strong link between sovereign risk and climate variables. Different authors have used different proxies for sovereign risk (e.g. yields on sovereign bonds, sovereign ratings) and several ways to proxy for climate change (e.g. rising temperatures, composite measures of resilience/vulnerability). The findings are fairly consistent across studies: the impact of climate related variables on sovereign risk is positive but there are important differences among different economies such as developed vs. developing. Therefore, we conclude that there is research space for further examining the possible uneven impact of climate related variables on sovereign risk by using an econometric approach that allows us to focus on non-linearities and to examine whether the relationship changes at percentiles other than the median (tail-dependence).

3. Data Statistical Properties and Econometric Methodology

3.1. Data Sources and Statistical Properties of Variables

In our empirical investigation we use a panel quantile framework to examine the effects of temperature (*temp*) and precipitation (*precip*) on sovereign yields (*yield*). Our sample includes 20 eurozone members over the period 1980M1 – 2023M4. Table 1 reports the notation of each variable as well as the corresponding source and link.

Table 1. Variables and Sources of Variables.

Notation	Variable	Source and link
yield	Long-term sovereign yields based on EMU convergence criterion series	Eurostat; Open product page
temp	Monthly average mean surface air temperature	Climate Change Knowledge Portal – World Bank https://climateknowledgeportal.worldbank.org/download-data
precip	Monthly precipitation level (country average)	Climate Engine; https://app.climateengine.org/climateEngine

Table 2 presents the summary statistics for the variables. Skewness is a measure of symmetry of the probability distribution of a variable about its mean, while kurtosis is a measure of tail heaviness of the distribution, measuring the weight of the tails relative to the rest of the distribution. Our data reveals that, with respect to skewness, the *yields* and *precip* series are highly positively skewed, while the *temp* series is symmetric. Further, considering kurtosis, the *yields* and *precip* series are leptokurtic, while the *temp* series is mesokurtic. Overall, we conclude that the *yields* and *precip* series exhibit characteristics of a non-normal distribution, while the *temp* series is consistent with a normal distribution. Therefore, given the signs of nonlinearities, we need to apply econometric techniques that depart form the standard Gaussian assumptions.

Table 2. Summary statistics.

Variable	No. of obs.	Mean	Median	Variance	Min	Max	Skewness	Kurtosis
yield	7452	5.009	4.39	15.798	-0.9	29.24	1.350	5.585
temp	10078	9.863	9.555	64.094	-16.29	29.74	-0.052	2.498
precip	10225	57.927	52.22	1974.666	0.119	355.64	1.292	5.794

3.2. Econometric Methodology

The previous data analysis revealed the existence of possible asymmetric features in the panel, which indicates the need for applying econometric techniques that allows us to examine the temperature and precipitation effects across the distribution of the sovereign yields. Specifically, we need to distinguish among climate effects on different quantiles of the distribution of the dependent variable. Given that sovereign yields indicate the level of risk of each economy, we will distinguish among climate effects on low risk economies (lower quantiles of the dependent variable), normal risk economies (middle quantiles) and high-risk economies (upper quantiles).

Our econometric methodology consists of the following steps: First, to examine the order of integration of our variables, we conduct various panel unit root tests, namely Phillips-Perron and Dickey Fuller Fisher – type tests (Choi, 2001), Im – Pesaran – Shin (2003) test and Pesaran (2007) test. The latter will lead us to the decision concerning the formulation of our modelling specification. Second, we apply cross sectional independence (Pesaran, 2004; Pesaran & Xie, 2021) tests and the slope homogeneity test of Pesaran and Yamagata (2008) in order to choose the proper econometric methodology. Third, considering the indications of the previous two steps, together with the data analysis, we apply various mean panel estimation techniques of heterogeneous coefficients in large

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panels allowing for dependence between cross-sectional units. More specifically, we consider the OLS location and scale estimator, the Cross-Sectional Autoregressive Distributed Lag (CS-ARDL) estimator (Chudik et. al 2016), the Mean – Group (MG) estimator (Pesaran and Smith, 1995) and the Dynamic Common-Correlated Effects (DCCE) estimator (Chudik and Pesaran, 2015). Forth, to consider possible nonlinearities and account for differences in the impact of the climate variables along different levels of sovereign risk, we apply the quantile via moments methodology of Machado and Santos Silva (2019), by developing a location – scale model of the following form:

$$yields_{it} = a_{it} + X_{it}'\beta + (\delta_i + Z_{it}'\gamma)U_{it} \qquad (1)$$

where $\Pr\{\delta_i + Z_{it}'\gamma > 0\} = 1$ and $(a_i, \delta_i), i = 1, \ldots, n$, capture the individual i fixed effects and Z is vector of known differentiable transformations of X. The sequence $\{X_{it}\}$ is strictly exogenous, i.i.d for any fixed i and independent across i, and denotes a vector of the independent variables, namely $temp$, $temp\_sq$ for the temperature specification model and $precip$, $precip\_sq$ for the precipitation specification model. U_{it} are i.i.d., statistically independent of X_{it} and normalized to satisfy that $E(U) = 0$ and $E(|U|) = 1$. Given the above assumptions, equation (1) gives that:

$$Q_{yields}(\tau/DC_{it}) = \big(a_i + \delta_i q(\tau)\big) + X_{it}'\beta + Z_{it}'\gamma q(\tau) \qquad (2)$$

In equation (2) the quantile – τ fixed effect for individual i is given by the coefficient $a_i(\tau) \equiv a_i + \delta_i q(\tau)$ and can be estimated as follows:

$$\hat{a}_i(\tau) = \frac{1}{T}\sum_{t=1}^{T}(yields_{it} - X_{it}'\hat{\beta}) + \hat{q}\frac{1}{T}\sum_{t=1}^{T}\left(\left|\widehat{R_{it}}\right| - Z_{it}'\hat{\gamma}\right) \qquad (3)$$

where, R denote the estimated residuals $\hat{R}_{it} = yields_{it} - \hat{a}_i - X_{it}'\hat{\beta}$. It should be noted that in our empirical analysis we use alternative specifications of the above model with respect to the use of the dependent and the independent variables.

The main advantages of the above methodology are the following: First, quantile regression analysis provides a more comprehensive description of the conditional distribution than the ordinary mean approach and it is a more robust econometric technique in the presence of conditional heterogeneity and departures from the Gaussian conditions. Second, the quantile via moments methodology accounts for possible cross-sectional dependence and slope heterogeneity. Finally, the main advantage of this methodology is that it allows the use of methods that are valid in the estimation of conditional means, while still providing information on how the regressors affect the entire conditional distribution (Machado and Santos Silva (2019)).

4. Empirical Analysis and Discussion

We frame our empirical analysis as follows: Initially, we present our preliminary findings, which include unit root tests, cross-sectional independence and slope homogeneity tests. We then proceed to apply various panel mean regression estimators and finally we focus on our main analysis employing the quantile via moments econometric methodology. The above structure allows us to derive a clear picture with respect to the development of the modelling specification that better fits the climate impact of sovereign risk, as well as to explore all possible asymmetries.

4.1. Preliminary Results

The results of our unit root tests are presented in Table 3. The null hypothesis in these tests is that the panels include a unit root (non-stationary data). Fisher-type tests, both in the form of Phillips-Perron and Dickey Fuller Fisher, as developed by Choi (2001) test for panel-data unit roots from a meta-analysis perspective, namely they conduct unit-root tests for each panel individually and then combine the p-values from these tests to produce an overall test. To mitigate the impact of possible cross-sectional dependence we follow Levin, Lin and Chu's (2002) procedure which, for each time period, computes the mean of the series across panels and subtracts this mean from the series. Next, we apply the Im – Pesaran – Shin (2003) test to account for the possibility that our panel dataset does not share a common autoregressive parameter. Finally, to check the robustness of our previous findings we use the Pesaran (2007) unit root test. In all cases our results indicate a rejection of the null hypothesis of non – stationarity.

Table 3. Panel data unit root tests.

Variable	Fisher type (P-Perron) test	Fisher type (DFuller) test	Im-Pesaran-Shin test	Pesaran test
yields	-20.478***	-17.374***	-6.8688***	-11.980***
temp	-36.340***	-36.340***	-43.284***	-21.864***
precip	-89.304***	-89.304***	-70.6252***	-21.864***

Notes: P values are in parentheses. *, **, *** denote significance at 10%, 5% and 1% level, respectively.

At the next step we procced with the of cross-sectional independence tests, to examine the null hypothesis that the error terms are characterized by independence across different cross sectional – units. According to Philips and Sul (2003) Chudik and Pesaran (2013), and Pesaran (2016) ignoring cross-sectional dependence of errors leads to serious limitations in the estimation efficiency. Moreover, the empirical experience shows that cross sectional dependence in economics is usually the rule rather than the exception. Further, as mentioned by De Hoyos and Sarafidis (2006), cross sectional dependence may be caused by the presence of common shocks and unobserved components incorporated in the error term. Subsequently, to account for possible common shocks with heterogeneous impact across countries and/or for local spillover effects between countries (Eberhardt and Teal, 2011) we choose to apply the Pesaran (2004) CD test, which assumes cross-sectional independence as the null hypothesis. We apply the test for the variables, the temperature model and the precipitation model. Our results, reported in the second column of Table 4, show that the null hypothesis of cross – sectional independence is rejected. Further, to examine whether the cross – sectional dependence is weak, we apply the bias corrected CD* test from Pesaran & Xie (2021). The alternative hypothesis in this test is that cross – sectional dependence is strong. Our results, reported in the third column of Table 4, indicate that we reject the null hypothesis, namely our cross – sectional dependence is strong.

Table 4. Cross sectional independence test and slope homogeneity test.

Variable	Cross sectional independence		Slope homogeneity
	Pesaran CD test	Pesaran & Xie test	Pesaran and Yamagata test
temp model	167.75*** abs (corr): 0.731	-16.08*** (0.000)	-3.002*** (0.003)
precip model	175.04*** abs (corr): 0.783	-16.12*** (0.000)	154.496*** (0.000)
yields	165.06*** abs (corr): 0.709	-	-
temp	155.02*** abs(corr): 0.699	-	-
precip	21.19*** abs(corr): 0.178	-	-

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Notes: Average absolute values of the off-diagonal elements are in parentheses of the cross-sectional independence tests. *, **, *** denote significance at 10%, 5% and 1% level, respectively. p-values are in parentheses.

Next, we test for slope homogeneity. In case a model consists of heterogeneous slopes, imposing slope homogeneity yields inconsistent and biased results. We perform a test that is a standardized version of Swamy's (1970) test for slope homogeneity presented by Pesaran and Yamagata (2008). A main advantage of the test is that it can be used for both balanced and unbalanced panels. The null hypothesis of the model assumes slope homogeneity across cross-sectional units, namely the slope coefficients are identical. It should be noted that we use the specification of the heteroskedasticity and autocorrelation consistent (HAC) test statistic of Blomquist and Westerlund (2013) and in addition, following Andrews and Monahan (1992), we also perform pre-whitening to reduce sample bias in the HAC estimation. Our results, reported in the fourth column of Table 4, show that, in all cases, the null hypothesis of slope homogeneity is rejected.

4.2. Main Results: Mean and Quantile via Moments Analysis

The nonlinear features of our data suggest that we should choose a modelling specification able to consider the effects of climate variables on the sovereign yields, allowing for differences in magnitude (e.g. extremely high temperatures or low precipitation/drought). In addition, the specification should account for an in-depth analysis of the climate effects on the entire distribution of the sovereign yields. Moreover, the results of the cross – sectional independence tests, as well as the slope homogeneity test, point to the need to choose an econometric technique consistent with strong dependence in the error terms and slope heterogeneity. To account for the above issues, we choose a quadratic modelling specification and apply various panel econometric techniques that focus on the entire distribution of the dependent variable and are also sensitive to short and long run effects.

Table 5 presents the estimation results of various mean panel time – series models with heterogenous slopes, both for the temperature and the precipitation model. Columns 2 – 5 report the results of the location and scale estimators (OLS) as mentioned in Machado and Santos Silva (2019). The statistically significant coefficients on $temp_{sq}$ of 0.0022 for the location estimator and 0.0012 for the scale estimator, as well as on $precip_{sq}$, of 0.000021 for the location and 0.000022 for the scale estimators respectively from the quadratic econometric models indicate their convexity. More specifically, the impact of the climate variables becomes negative at extreme negative values of temperature and precipitation and positive at extreme positive values. However, it should also be noted that the magnitude of the impact of precipitation is low. Next, we apply the the Mean – Group (MG) estimator (Pesaran and Smith, 1995) that accounts for heterogeneous slopes (columns 6 and 7). In this case, we observe that the impact of $temp_{sq}$ (0.00106) is positive and statistically significant while the impact of $precip_{sq}$ (0.0000164) is insignificant. The same holds when it comes to the the Dynamic Common-Correlated Effects (DCCE) estimator (Chudik and Pesaran, 2015), which accounts for the endogeneity that occurs when a lag of the dependent variable is added to the model specification. Specifically, we observe (columns 8 and 9) that the impact of $temp_{sq}$ (0.0023) is statistically significant, while the impact of $precip_{sq}$ (0.0000156) is not. Finally, columns 9 and 10 report the results of the Cross-Sectional Autoregressive Distributed Lag (CS-ARDL) estimator (Chudik et. al 2016). A main advantage of the CS-ARDL estimator is that it distinguishes between long and short run effects. According to our estimations, the coefficients on $temp_{sq}$ are positive and statistically significant both in the short (0.0036) and long (0.0029) run period while the coefficients on the $precip_{sq}$, both for the short and long run period, are statistically insignificant. Overall, the mean panel time series estimations reveal that the impact of temperature on sovereign yields is quadratic and specifically of convex shape, while the results concerning the impact of precipitation are mixed.

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Table 5. Estimating panel time-series models with heterogeneous slopes.

	Temp model	Precip. model	Temp model	Precip. model	Temp model	Precip. model	Temp model	Precip. model	Temp. model		Precip. model	
Ind. var.	Location estimator	Location estimator	Scale estimator	Scale estimator	MG estimator	MG estimator	DCCE estimator	DCCE estimator	CS-ARDL estimator		CS-ARDL estimator	
									Short run	Long run	Short run	Long run
temp	0.0432***		-0.0020		-0.0385***		-0.0421***		-0.0590**	-1.0590***		
	(0.008)		(0.0067)		(0.0124)		(0.0136)		(0.0241)	(0.0241)		
temp_sq.	0.0022***		0.0012***		0.00106*		0.0023***		0.0036***	0.0029**		
	(0.0003)		(0.0003)		(0.000550)		(0.000692)		(0.0013)	(0.0012)		
l.temp									-0.0440***	-0.0405***		
									(0.0113)	(0.0098)		
l.temp_sq.									0.0014***	0.00134***		
									(0.00046)	(0.00041)		
Constant	4.330***	5.363***	1.187***	1.571***	4.939***	4.613***	5.1399***	4.6009***	5.3822	5.0572***	4.6273***	4.6135***
	(0.0600)	(0.0646)	(0.0471)	(0.0532)	(0.400)	(0.393)	(0.456574)	(0.41939)	(0.4917)	(0.4311)	(0.4820)	(0.4762)
precip		-0.0058***		-0.0058***		-0.000680		-0.000621			-0.0011	-1.0010***
		(0.0012)		(0.0012)		(0.00299)		(0.00297)			(0.0031)	(0.00316)
precip_sq.		0.000021***		0.000022***		0.0000164		0.0000156			0.0000183	0.0000169
		(6.11e-06)		(6.11e-06)		(2.36e-05)		(0.000022)			(0.0000248)	(0.0000244)
l.precip											-0.00147	-0.001314
											(0.003269)	(0.003251)
l.precip_sq.											0.0000191	0.0000179
											(0.000023)	(0.0000228)
Obs.	7,131	7,334	7,131	7,334	7,131	7,334	7,131	7,334	7,125		7,303	
Number of countries	20	20	20	20	20	20	20	20	20		20	

Notes: Robust standard errors in parentheses. *, **, *** denote significance at 10%, 5% and 1% level, respectively.

Even though the analysis so far has assumed a quadratic impact of the climate variables, it has not considered possible asymmetries along the distribution of the dependent variable. Therefore, as a next step we apply the Quantile via Moments methodology of Machado and Santos Silva (2019), with fixed effects, that additionally accounts both for cross – sectional dependence and conditional heterogeneity. Tables 6 and 7 present the estimation results of the pairwise relationships of $temp_{sq}$ and $precip_{sq}$ with sovereign yields, respectively. Following Lolos et. al (2021), we categorize the quantiles of sovereign yields into three regimes, namely a low-risk economy $[\tau = (0.10, 0.20, 0.30)]$, a normal – risk economy $[\tau = (0.40, 0.50, 0.60)]$ and a high-risk economy $[\tau\ (0.70, 0.80, 0.90)]$. Further, as before, we use a quadratic specification to account for the impact of the climate variables ($temp_{sq}$, $precip_{sq}$) on sovereign yields. Therefore, the quantile via moments methodology combined with the quadratic specification account for dual nonlinearities. First, by considering nonlinearities caused by the variation in the dependent variable (quantile method) and second by considering nonlinearities caused by the variation of the independent variable (quadratic specification).

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Consequently, in line with Kiley (2021), to calculate the combined coefficients of temperature and precipitation we use various thresholds corresponding to extreme conditions.

Table 6. Estimation results (Quantiles via Moments) for the quadratic model of temperature, with fixed effects. Dependent variable is Sov_yields.

	Low risk economy			Normal risk economy			High risk economy		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ind. var.	qtile_10	qtile_20	qtile_30	qtile_40	qtile_50	qtile_60	qtile_70	qtile_80	qtile_90
temp	0.0456***	0.0451***	0.0447***	0.0443***	0.0439***	0.0433***	0.0424***	0.0412***	0.0394**
	(0.00813)	(0.0077)	(0.007)	(0.0076)	(0.008)	(0.0088)	(0.0105)	(0.0136)	(0.0186)
temp_sq.	0.000781**	0.00106***	0.0012***	0.0015***	0.0017***	0.0021***	0.0026***	0.0033***	0.004***
	(0.000335)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0006)	(0.0008)
Cons.	2.974***	3.239***	3.447***	3.672***	3.940***	4.297***	4.773***	5.469***	6.498***
	(0.0503)	(0.0455)	(0.0451)	(0.0476)	(0.0526)	(0.0624)	(0.0769)	(0.0980)	(0.137)
Obs.	7,131	7,131	7,131	7,131	7,131	7,131	7,131	7,131	7,131
Cumulative temperature effects									
temp.=15.97 °C, (75% percentile)									
Coef.	0.0705***	0.0788***	0.0854***	0.0926***	0.1010***	0.1123***	0.1274***	0.1494***	0.1820***
	(0.0053)	(0.0051)	(0.0052)	(0.0056)	(0.0064)	(0.0079)	(0.0101)	(0.0136)	(0.0191)
temp.=23.1 °C, (95% percentile)									
Coef.	0.08164***	0.0939***	0.1036***	0.1141***	0.1265***	0.1432***	0.1653***	0.1977***	0.2456***
	(0.0092)	(0.0088)	(0.0089)	(0.0094)	(0.1051)	(0.0125)	(0.0158)	(0.0211)	(0.0295)
temp.=27.25 °C, (99% percentile)									
Coef.	0.08813***	0.1027***	0.1142***	0.1267***	0.1415***	0.1612***	0.1874***	0.2258***	0.2827***
	(0.0118)	(0.0112)	(0.0113)	(0.0119)	(0.0131)	(0.0155)	(0.0194)	(0.0259)	(0.0362)

Notes: Robust standard errors in parentheses. *, **, *** denote significance at 10%, 5% and 1% level, respectively.

Table 7. Estimation results (Quantiles via Moments) for the quadratic model of precipitation, with fixed effects. Dependent variable is Sov_yields.

	Low risk economy			Normal risk economy			High risk economy		
	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Ind. Var	qtile_10	qtile_20	qtile_30	qtile_40	qtile_50	qtile_60	qtile_70	qtile_80	qtile_90
precip	-0.0028**	-0.0044***	-0.0054***	-0.0064***	-0.0076***	-0.0092***	-0.0115***	-0.0150***	-0.0205***
	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0015)	(0.00183)	(0.0024)	(0.00353)
precip_sq.	1.99e-05***	2.58e-05***	2.94e-05***	3.31e-05***	3.76e-05***	4.32e-05***	5.15e-05***	6.43e-05***	8.44e-05***
	(7.62e-06)	(7.08e-06)	(6.94e-06)	(6.96e-06)	(7.19e-06)	(7.77e-06)	(9.09e-06)	(1.18e-05)	(1.67e-05)
Cons.	3.529***	3.956***	4.218***	4.489***	4.817***	5.225***	5.832***	6.769***	8.235***
	(0.0553)	(0.0442)	(0.0437)	(0.0468)	(0.0542)	(0.0652)	(0.0860)	(0.116)	(0.161)
Obs.	7,334	7,334	7,334	7,334	7,334	7,334	7,334	7,334	7,334
Cumulative precipitation effects									
precip.=1.24, (1% percentile)									
Coef.	-0.00282**	-0.00441***	-0.00537***	-0.00637***	-0.00759***	-0.00910***	-0.01135***	-0.0148***	-0.0202***
	(0.00137)	(0.00122)	(0.00120)	(0.00123)	(0.00132)	(0.00148)	(0.00181)	(0.00242)	(0.00349)
precip.=4.39, (5% percentile)									
Coef.	-0.00269**	-0.00424***	-0.00519***	-0.00617***	-0.0073***	-0.0088***	-0.0110***	-0.0144***	-0.0197***
	(0.00127)	(0.001178)	(0.00116)	(0.00119)	(0.00127)	(0.00143)	(0.0017)	(0.00235)	(0.00339)
precip.=22.52, (25% percentile)									
Coef.	-0.001976*	-0.00331***	-0.00412***	-0.00497***	-0.00599***	-0.00726	-0.00915***	-0.0121***	-0.0166***
	(0.001025)	(0.000948)	(0.000943)	(0.000971)	(0.001047)	(0.001189)	(0.001469)	(0.00198)	(0.00285)

Notes: Robust standard errors in parentheses. *, **, *** denote significance at 10%, 5% and 1% level, respectively.

Specifically, for the pairwise relationship between temperature and sovereign yields (Table 6) we choose as thresholds the 75th (15.97 °C), 95th (23.1 °C) and 99th (27.25 °C) percentiles. The choice of these percentiles shows that we are interested in focusing on the impact of high temperatures on the sovereign yields, as climate change is expected to increase average temperatures. We observe that for higher levels of temperature the effect on sovereign risk is positive, as excepted by the convexity of our quadratic model specification. Additionally, the impact increases as we move from the lower

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quantiles (low risk economy) towards the upper quantiles (high risk economy). The same pattern is repeated for all three selected percentiles. Specifically, for the 75th percentile the impact of temperature at the lowest bound (extreme low risk economy) is 0.0705 and after a gradual consistent increase reaches the upper bound (extreme high-risk economy) which is equal to 0.1820. The corresponding lower bound for the 95th percentile is 0.08164, while the upper bound is 0.2456. Finally, for the 99th percentile, the lower bound is 0.08813, while the upper bound is 0.2827.

When it comes to the pairwise relationship between precipitation and sovereign yields (Table 7) we choose as thresholds the 25th (22.52 °C), 5th (4.39 °C) and 1st (1.24 °C) percentiles. The choice of these percentiles shows that we are focusing on the impact of low precipitation levels (drought) on sovereign yields, as climate change is expected to decrease the frequency of precipitations. We observe that for lower levels of precipitation the effect on sovereign risk is negative, as excepted by the convexity of our quadratic model specification. Additionally, the impact increases as we move from the lower quantiles (low risk economy) towards the upper quantiles (high risk economy). The same path is repeated for all three selected percentiles. Specifically, for the 25th percentile the impact of precipitation at the lowest bound (extreme low risk economy) is -0.001976 and after a gradual consistent increase, in absolute terms, reaches the upper bound (extreme high-risk economy) which is equal to -0.0166. The corresponding lower bound for the 5th percentile is -0.00269, while the upper bound is -0.0197. Finally, for the 1st percentile, the lower bound is -0.00282, while the upper bound is -0.0202. It should be noted that the impact of precipitation, according to the quantile approach, is found to be statistically significant, in contrast to the findings of the mean panel estimators, where the results were mixed. The latter finding is mainly because the quantile via moments estimator can consider nonlinear features along the distribution of the sovereign yield and therefore is not limited to the mean. Moreover, the estimator accounts for both strong dependence in the error terms and slope heterogeneity.

According to the above findings, the impact of temperature on sovereign yields increases in magnitude as: (a) the sovereign risk rises and (b) the temperature rises. Further, when it comes to the impact of precipitation on sovereign yields, it increases in magnitude as: (a) the sovereign risk rises and (b) the precipitation decreases. These findings have the following important policy implications: climate change, in the sense of an increase in the temperature: (a) will increase the sovereign risk of all countries, but the magnitude of the impact will be higher for the countries that are characterized by a higher sovereign risk level and (b) will increase the sovereign risk of the hotter countries. In addition, climate change, in the sense of a decrease in precipitation: (a) will increase the sovereign risk of all countries, but the magnitude of the impact will be higher for the countries that are characterized by a higher sovereign risk level and (b) will increase the sovereign risk of the countries that already face drought issues. Our findings are in line with Cevik and Jalles (2020), Beirne et. al (2021a), Cevik and Jalles (2022a,b) and Assab (2023) who show that the impact of extreme weather conditions are more pronounced in more vulnerable economies, where the vulnerability takes different forms. However, to the best of our knowledge the impact of extreme weather conditions along the distribution of the sovereign yields and assuming a quadratic modelling specification, has not been examined before.

5. Conclusions

In this study we examine the relationship among sovereign yield, temperature and precipitation using a large monthly panel data set which consists of 20 eurozone members, over the period 1980M1 – 2023M4. To account for possible asymmetries along the distribution of the independent variables we assume a quadratic modelling specification. Initially, we apply various mean panel estimation techniques of heterogeneous coefficients allowing for dependence between cross-sectional units [among others, the Dynamic Common-Correlated Effects (DCCE) estimator (Chudik and Pesaran, 2015) and the Cross-Sectional Autoregressive Distributed Lag (CS-ARDL) estimator (Chudik et. al 2016)]. At a next step, to consider possible nonlinearities in the distribution of the dependent variable (sovereign risk) we apply the quantile via moments methodology of Machado and Santos Silva (2019).

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We contribute to the existing literature in two ways. First, by applying a quantile methodology, assuming a quadratic modelling specification, that accounts both for cross – sectional dependence and slope heterogeneity. This method allows for a more in-depth analysis of the climate effects along the distribution of the sovereign yields, especially in the presence of non-normally distributed data. Second, by finding that climate change will increase the sovereign risk of all countries, but the magnitude of the impact will be higher for the countries that are already characterized by a higher sovereign risk level and/or face extreme weather conditions (hotter countries and/or countries with low levels of precipitation).

The main findings of our research are the following: First, we find strong evidence of a dual non-linear relationship between the variables under study. Specifically, the impact of temperature and precipitation on sovereign yields varies because of nonlinearities caused by the variation in the dependent variable (quantile method) and by nonlinearities caused due to the variation of the independent variable (quadratic specification). The mean estimators cannot identify the quadratic relationship between precipitation and sovereign yields due to limitations arising from their mean approach properties. Second, we find that the impact of temperature on sovereign yields increases in magnitude as the sovereign risk rises and/or as the temperature rises. Additionally, the impact of precipitation on sovereign yields increases in magnitude as the sovereign risk rises and/or the precipitation decreases.

The above findings have important policy implications as they indicate that climate change is expected to affect more severely countries that already face high economic risks and are characterized by extreme weather conditions (higher temperatures, droughts). This highlights the uneven impact of environmental variables on economic ones. More work needs to be done on this front and will guide our future research.

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