DOI: 10.1111/fmii.12192

ORIGINAL ARTICLE

FINANCIAL MARKETS, INSTITUTIONS & INSTRUMENTS · NEW YORK UNIVERSITY SALOMON CENTER · WILEY

Air temperature and sovereign bond returns

Renatas Kizys[1] | Wael Rouatbi[2] | Zaghum Umar[3,5] | Adam Zaremba[2,4,6]

[1]Department of Banking and Finance, Southampton Business School, University of Southampton, Southampton, UK

[2]Montpellier Business School, Montpellier, France

[3]College of Business, Zayed University, Abu Dhabi, United Arab Emirates

[4]Department of Investment and Financial Markets, Institute of Finance, Poznan University of Economics and Business, Poznań, Poland

[5]Adnan Kassar School of Business, Lebanese American University, Beirut, Lebanon

[6]Department of Finance and Tax, Faculty of Commerce, University of Cape Town, Cape Town, South Africa

Correspondence
Renatas Kizys, Department of Banking and Finance, Southampton Business School, University of Southampton, Highfield Campus, Southampton SO17 1BJ, UK.
Email: r.kizys@soton.ac.uk

Funding information
National Science Center of Poland, Grant/Award Number: 2019/33/B/HS4/01021

Abstract

The relationship between air temperature and sovereign bond returns is founded on competing paradigms: macroeconomic, behavioral and energy demand-based. Which of these theoretical mechanisms receives support from data? To answer this, we examined four decades of bond data from 31 countries. Overall, daily temperature positively affects government bond returns. A 10°F rise leads to an increase in sovereign bond returns between 0.22 and 0.85 basis points. We also document evidence of asymmetric and nonlinear price responses to both temperature levels and shocks. Our results survive a battery of robustness checks and lend support to the macroeconomic and behavioral paradigms, albeit not the energy demand-based view.

KEYWORDS
air temperature, asset pricing anomalies, behavioral paradigm, energy demand-based view, international government bond markets, macroeconomic channels, risk aversion, seasonal binary variable l affective disorder, sovereign bond returns

JEL CLASSIFICATION
G10, G12, G14, G15, Q54

1 | INTRODUCTION

Do investors in sovereign bonds price information regarding global warming and temperature rises? The purpose of this study is to empirically address this question by examining four decades of sovereign bond returns data from 31 countries worldwide. The theoretical foundation of our investigation of the relation between air temperature and sovereign bond returns rests upon three competing paradigms. First, the macroeconomic paradigm suggests that temperature rises can lead to a devaluation of risky financial investments, as well as a revaluation of relatively safe assets through several macroeconomic channels; this is because climate change that manifests in higher temperatures can erode the value of patents, deplete capital stock and dampen labor productivity (see, e.g., Donadelli et al., 2021; Hübler et al., 2008). Second, the behavioral paradigm asserts that the weather affects investors' moods and behavior.[1] For instance, the air temperature may influence judgment formation and risk aversion, which affects stock returns (see, e.g., Cao & Wei, 2005a). The macroeconomic and behavioral views predict that temperature rises will trigger investors' "flight to security," whereby they rebalance their financial investment portfolios from relatively risky (such as stocks) to relatively risk-free assets (such as bonds). Their decisions to invest in sovereign bonds aim to secure a constant flow of income in episodes of heightened multidimensional uncertainty, with a particular emphasis on rising temperatures and global warming.

Third, the energy demand-based paradigm, in turn, implies that both cold and hot temperature shocks lead to increased demand by households and industries for energy used for heating and cooling, respectively. This translates into increased demand for hedging in the market of weather derivatives, which then allows energy users to insure against both climate change and weather risks (Weagley, 2019). The ensuing rise in the prices of energy and weather derivatives drives up operational costs for companies, which, as a consequence, may result in them needing to borrow to cover these increased costs. Thus, equity investments in these companies become more leveraged and, therefore, riskier. If the increase in equity investment risk is not compensated with a higher reward, investors may switch from stocks to fixed-income securities. As a result, both significant temperature decreases and increases can generate higher sovereign bond returns.

Although the relation between temperature and sovereign bond returns has solid theoretical foundations, it is surprising that empirical insights into this relation are underwhelming. It is noteworthy that such an inquiry can potentially have a significant practical value for the industry of financial services. Indeed, it is recognized in financial media that the investment value of sovereign bonds is exposed to a range of climate change risks (such as transition and physical hazards) that the participants of the sovereign bond market have largely neglected.[2]

Which of the competing paradigms is supported by the data? We seek to ascertain whether and, if so, how air temperature affects sovereign bond returns around the world. There is a dearth of research into the pricing of temperature changes in the sovereign bond market. Our study intends to bridge this gap within the related literature.

Within the existing body of empirical research on temperature-driven stock price variation, little has been written on the source of the increased demand for stocks on cold days. The macroeconomic theory implies that a lower temperature is associated with larger research and development (R&D) spending, which could translate into a higher long-run growth rate and, therefore, triggers an appreciation of financial assets. Under the behavioral view, if investors become more risk-taking during cold days, they will be more willing to invest in riskier assets—such as stocks. Taking this together, if the equity prices abnormally surge during cold days, the additional purchases are typically funded from external sources. In an open financial market, such a large-scale repricing of the entire equity market may be accompanied by capital movements between asset classes. In other words, investors may need to sell some other securities to reallocate their funds to equity markets. Arguably, the additional demand in the equity market during cold days is funded by the reverse mechanism in the government bond market. In other words, just as a lower temperature increases investors' appetite for a risky stock, it decreases their appetite for safe securities, that is, sovereign bonds.[3] Moreover, high-temperature levels may lead to a relatively lower demand for stocks than for safer bonds. Consequently, while the air temperature is *negatively* associated with stock returns, it is expected to be *positively* associated with bond returns. In short, the higher temperature should be associated with higher bond returns—and vice versa.

To verify these conjectures, we examine four decades of bond market data from across 31 countries worldwide. We run panel regressions to evaluate the impact of daily air temperature on daily sovereign bond returns. To assure robustness, we control for an array of bond characteristics, macroeconomic variables, time variation and seasonal effects. In addition to this, we also consider different types of bonds, ways of temperature measurement, different model estimation methods and additional control variables.

It is important to note that the sovereign bond market is distinct from the stock market, and, thus, any earlier findings from the stock market may not necessarily carry over to the bond market. The decision to focus on sovereign bonds in this study is motivated by several factors. First, sovereign bonds are susceptible to default risk, which can significantly affect bond returns, particularly during periods of stress (Bai et al., 2016). Second, bondholders exhibit higher sensitivity to downside risk than stockholders and often require higher returns (Kinateder & Papavassiliou, 2019). These characteristics make sovereign bonds an interesting subject of study, as they are affected differently by temperature rises and global warming compared to stocks.

In addition to being an interesting subject of study, sovereign bonds are also an important investment class. As of 2020, the global bond market is valued at over $128.3 trillion, making it one of the largest markets in the world (ICMA, 2020). Sovereign bonds make up a significant portion of this market and are widely held by institutional investors such as pension funds, insurance companies and central banks. As global warming and temperature rises are expected to have a significant impact on the global economy, understanding the relationship between these factors and sovereign bond returns can provide valuable insights for investors and policymakers.

The principal findings can be summarized as follows. First, the air temperature positively affects sovereign bond returns. Our empirical models, founded on the assumption of a linear relationship between temperature and bond returns, show that increasing the temperature by 10°F raises the daily returns on 10-year government bonds by 0.34–0.50 basis points. Moreover, when augmented with the seasonal affective disorder (SAD) variable, our models reveal a similar response of sovereign bond returns that ranges from 0.35 to 0.55 basis points. Furthermore, other model variations that control for the lagged dependent variable show a positive temperature effect that ranges between 0.32 and 0.48 basis points, which endorses our baseline results. The effect is statistically significant and cannot be subsumed by a range of control variables. Accounting for country-fixed effects confirms that our findings cannot be explained by any international variation in temperature. In addition, the results hold when considering bonds of various maturities and different temperature proxies and surviving alternative estimation methods. Our main findings remain intact when the detrended temperature replaces the temperature level. Overall—across all our specifications—the impact of a 10°F temperature increase ranges between 0.22 and 0.85 basis points, supporting both the macroeconomic and the behavioral paradigms.

Turning to a quadratic relationship between temperature and bond returns, our research findings show that a 10°F temperature increase above the average temperature of 58.58°F commands a positive effect of 0.535 basis points. The quadratic models that control for SAD show statistically weaker (albeit of the same order of magnitude) effects on bond returns. For instance, the impact of a 10°F rise in temperature above the average temperature (58.58°F) is estimated at 0.625 basis points. Overall, we find evidence of a U-shaped relationship between temperature and sovereign bond returns. This implies that, under the macroeconomic paradigm, economic losses caused by natural factors respond quadratically to temperature shifts.

Moving to the models that evaluate the effects of hot and cold temperature shocks, we find that sovereign bond returns respond positively to hot temperature shocks (proxied by the cooling degree day [CDD]) and negatively to cold temperature shocks (measured with the heating degree day [HDD]). These results do not agree with the energy demand-based view.

Our contribution to the related body of research is at least four-fold. First, we are the first to study the relationship between temperature and sovereign bond returns. Second, we provide evidence of non-linearities in the relationship between sovereign bond returns and temperature; in particular, the data indicate a U-shaped relation. Third, we show that the association between temperature and sovereign bond returns is not disrupted by investors' exposure to limited daylight in the fall and winter months. Last, we demonstrate that sovereign bond returns respond asymmetrically to positive and negative temperature shifts.

Overall, our research findings agree with both the macroeconomic and behavioral paradigms that posit a positive relationship between temperature rises and sovereign bond returns but do not support the energy-based view. Moreover, our study significantly adds to the asset pricing literature, founded on the macroeconomic, behavioral and energy demand-based paradigms. Whereas existing literature has explored this phenomenon in the stock market (Cao & Wei, 2005b; Chang et al., 2006; He & Ma, 2021; Tzouvanas et al., 2019; Yoon & Kang, 2009), other asset classes remain a largely unchartered territory. Andrikopoulos et al. (2019), who examined currencies, and Makkonen et al. (2021)—whose research centred on commodities—are the exceptions to this notion. To our knowledge, we are the first to investigate the temperature anomaly within international government bond returns.

Furthermore, our results complement prior studies on the weather conditions effects on financial markets around the world (Cao & Wei, 2005b; Chang et al., 2006; He & Ma, 2021; Hou et al., 2019; Sheikh et al., 2017; Yoon & Kang, 2009). For instance, the results of Cao and Wei (2005a) indicate that when the temperature is high, apathy dominates aggression, which, in turn, impedes risk-taking and results in lower stock returns. Our findings complete the picture by suggesting that higher temperature leads to lower risk-taking, which encourages investors to shift to safer financial instruments (sovereign bonds) and liquidate relatively riskier investments (stocks), resulting in higher sovereign bond returns and lower stock returns. By contrast, when the temperature is low, aggression dominates apathy and the propensity of investors to take more risks rises. Thus, investors will be more willing to invest in riskier assets (which increases stock returns) and abandon low-risk assets (which leads to lower sovereign bond returns).

The remainder of the article proceeds as follows. Section 2 reviews the related body of literature and formulates the hypotheses. In Section 3, we describe the data and outline the regression models. In Section 4, we discuss the empirical findings. Finally, in Section 5, we conclude the article.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Climate change has many different facets and attributes. It manifests not only in temperature rises but also in more prevalent extreme weather events (Katz, 2010). The frequency of excessively hot or cold days has vastly increased in recent decades (Lau & Nath, 2012; Vose et al., 2014). First, a rapidly mounting climate–economy literature has identified the widespread effects of temperature volatility on several matters. These include agriculture (Fisher et al., 2012), labor productivity (Chen & Yang, 2019; Graff Zivin & Neidell, 2014; Hübler et al., 2008), economic growth and production (Burke et al., 2015; Colacito et al., 2019; Dell et al., 2012), income level (Dell et al., 2009), professional decision-making (Heyes & Saberian, 2019) and R&D expenditure growth (Donadelli et al., 2021). Understanding the impact of these changes on financial markets has become one of the core objectives of modern finance (Giglio et al., 2021; Stroebel & Wurgler, 2021). We extend this stream of research by investigating the effect that air temperature can have on sovereign bond returns. Two main paradigms, macroeconomic and behavioral, suggest that such an effect exists.

The macroeconomic paradigm is based on the premise that rising temperatures may play a role in dampening economic activity in general and R&D expenditure growth in particular. In this vein, Bansal and Ochoa (2011) find that the utility costs arising from temperature variations and the dollar costs of insuring against such variations represent about 0.78% of world consumption and 2.46% of world GDP, respectively. Higher temperatures have also been shown to reduce economic growth (Colacito et al., 2019; Dell et al., 2012; Du et al., 2017), total personal income per capita (Deryugina & Hsiang, 2014) and green innovation (Hu et al., 2022). Moreover, Donadelli et al. (2021) provide evidence that shocks to global temperature trigger a negative impact on R&D expenditure growth. The authors identify three theoretical channels for this effect, namely, i) the patent obsolescence channel, ii) the labor productivity channel and iii) the capital quality channel.

Irrespective of the channel, a positive temperature shock triggers a negative valuation effect on financial market investments. As stated by Donadelli et al. (2021), both the value of risky financial investments and the risk-free interest rate show negative responses to a positive temperature shock. This is consistent with the findings of Bansal and Ochoa (2011), who document that rises in global temperature lead to lower equity valuations and higher risk premiums. More recently, Yan et al. (2022) use a sample of Chinese-listed companies over the 2007–2019 period and find that the continuous rise in temperature negatively and significantly affects stock returns. The negative responses of risky financial investments and the risk-free interest rate both signal investors' increased interest in debt instruments, such as sovereign bonds. They are willing to pay higher prices for sovereign bonds and, thus, are happy to accept lower interest rates. As a result, the rates of returns on sovereign bond investments are predicted to increase.

The behavioral paradigm, on the other hand, draws on the psychological literature dating back to the 1970s, which demonstrates that the weather affects human behavior.[4] More importantly, for our purposes, investor sentiment—and thus financial markets—can be influenced by weather-related factors such as sunshine and cloud coverage (Bassi et al., 2013; Hirshleifer & Shumway, 2003; Saunders, 1993), wind speed (Keef & Roush, 2002), humidity (Sariannidis et al., 2016), precipitation (Kaustia & Rantapuska, 2016) and air temperature (Bansal & Ochoa, 2011; Cao & Wei, 2005a; Floros, 2011; Keef & Roush, 2007; Peillex et al., 2021; Yan et al., 2022).

Among the different weather-related variables, air temperature is considered one of the most impactful drivers of mood and feelings. On the one hand, very low temperature not only impairs concentration or task-performing abilities (Pilcher et al., 2002) but, more importantly, may lead to aggression (see, e.g., Baron & Ransberger, 1978; Bell, 1981; Howarth & Hoffman, 1984; Palamarek & Rule, 1979). On the other hand, extreme heat can cause both aggression and apathy (Wyndham, 1969). Building on this psychological evidence, Cao and Wei (2005a) argue that low air temperature leads to more aggressive risk-taking and, thus, increases stock returns. Moreover, high temperature results in less predictable variations in relative risk aversion, which is driven by the balance between apathy and aggression. If aggression dominates apathy, the propensity of investors to take more risks rises, and—therefore—investors will be more willing to invest in riskier assets. By contrast, if apathy dominates, the degree of risk aversion increases and investors will prefer to shift to relatively safe financial instruments (such as bonds) and liquidate relatively riskier investments (such as stocks).

Having scrutinized data from several major equity markets (Australia, Canada, Germany, Japan, Sweden, Taiwan, UK and the United States), Cao and Wei (2005a) find evidence that supports their theoretical conjectures: when the temperature is high (low), apathy dominates aggression (aggression dominates apathy); this, in turn, impedes (increases) risk-taking and results in lower (higher) stock returns. Other studies demonstrate a similar pattern within numerous developed and emerging stock markets around the world (Cao & Wei, 2005b; Chang et al., 2006; He & Ma, 2021; Hou et al., 2019; Sheikh et al., 2017; Yoon & Kang, 2009). Although several controversies emerged with concerns about the behavioral mechanism behind this phenomenon (see, e.g., Jacobsen & Marquering, 2008, 2009; Kamstra et al., 2009), the overall conclusion appears unequivocal: A higher temperature coincides with lower stock returns (and vice versa). Therefore, under higher temperatures, one would expect investors to abandon relatively risky investments like stocks in favour of safer financial instruments such as sovereign bonds, resulting in higher sovereign bond returns. Based on these arguments, our first testable implication can be formally stated as hypothesis H1:

H1: Returns on sovereign bonds increase in response to positive temperature shifts.

Furthermore, we conjecture that the relation between air temperature and bond returns may feature non-linearities. This conjecture is based on prior research in psychology, which documents that high temperatures can lead to both apathy and aggression (see, e.g., Howarth & Hoffman, 1984; Palamarek & Rule, 1979; Wyndham, 1969). Thus, the effect of temperature on individuals' investment behavior depends on which of these behavioral outcomes dominate. For instance, Kamstra et al. (2003) show that a temperature rise exerts positive—albeit weak—effects on stock market returns in the United States, New Zealand and South Africa; however, it exerts insignificant effects in Australia, Canada, Germany, Japan and the UK. Such insignificant findings can be symptomatic of non-linearities in the relationship between temperature and stock market returns. One plausible explanation for this result is that the effect of a temperature rise is not constant but, instead, depends on the climate conditions that prevail in the country. In this vein, Bansal and Ochoa (2011) argue that the risk premium on investment in risky assets is higher in countries closer to the Equator and lower in countries further away from the Equator. In countries closer to the Equator, investors will switch to safer assets (e.g., sovereign bonds) if the perceived investment risk is not compensated with a higher return. Although some evidence shows that temperature can linearly translate into more considerable economic losses (Horowitz, 2009), such a linear relation is not necessarily supported by other studies. For instance, Du et al. (2017) agree with Horowitz (2009) that temperature harms economic growth and that such an effect appears nonlinear. Concretely, a negative relationship between temperature and economic growth occurs for temperatures higher than 6°C.

The presence of non-linearities is also informed by Tzouvanas et al. (2019), who model variations in the systemic risk of EU manufacturing companies as a quadratic function of temperature and provide evidence that the latter has a significant impact on systemic risk. Therefore, our models are designed to address nonlinear temperature effects on sovereign bond returns. Investments in sovereign bonds are incentivized by the prospect of quadratic losses to the economy caused by natural disasters; this can be transmitted to prices and returns on variable income securities, such as stocks. We would expect a U-shaped relation between both temperature and sovereign bond returns. Accordingly, our second testable implication can be formally stated as hypothesis H2:

H2: The response of returns of sovereign bonds to positive temperature shifts is U-shaped.

The presence of non-linearities is further supported by the energy-based paradigm, which sheds light on another channel through which temperature shifts can affect sovereign bond returns. The energy demand-based view implies that cold and hot temperature shocks increase the demand by households and businesses for energy that is used for both heating and cooling. Investors regard unexpected increases in energy demand as adverse shocks. This gives rise to a higher demand by firms for hedging in the market for weather derivatives to manage climate change and weather risks (Tzouvanas et al., 2019; Weagley, 2019). Energy demand arising from positive and negative energy shocks is reminiscent of the precautionary oil demand shock (or oil-specific demand shock) in the oil market, disentangled by Kilian (2009) from the oil supply shock and aggregate demand shock. Precautionary demand reflects the uncertainty about the shortfalls of expected supply relative to expected demand. If unexpected temperature shifts can drive changes in the precautionary demand for energy, companies may decide to hold higher oil inventories as both a convenience and insurance against future disruptions in the balance between demand and supply for oil. Importantly, returns on stock market investments respond negatively to changes in the precautionary demand for oil (Kilian & Park, 2009). Arguably, when investors fund fixed-income investments (e.g., sovereign bonds) by selling off variable-income assets (e.g., stocks), a positive response of sovereign bond returns can be expected.

To sum up, both hot and cold temperature shocks lead to an increase in energy demand and prices, which translates into higher operational costs for firms. More expensive energy inputs may require borrowing. As a result, firms become more leveraged and, thus, risky, and investors may decide to rebalance their portfolios from stocks to sovereign bonds, which positively affects sovereign bond returns. These arguments give rise to our third testable implication, stated as hypothesis H3:

H3: Cold and hot temperature shocks cause positive effects on sovereign bond returns.

3 | DATA AND METHODS

3.1 | Sample and data sources

Our empirical analysis draws on total daily returns on Datastream Government Bond Indices. Our bond universe consists of 2-, 5-, 10-, 20- and 30-year sovereign bonds of 31 developed and emerging countries from Africa, Asia, Europe, North America and Oceania. Table 1 lists the set of countries covered in this study. The sample period spans from 1 January 1980 to 18 September 2020.

In our primary analysis, we focus on 10-year bonds. This maturity is the most common choice in international asset pricing studies; this is due to the broad global coverage and high liquidity when compared to shorter- or longer-maturity bonds (see, e.g., Baltussen et al., 2021; Geczy & Samonov, 2017; Ilmanen et al., 2021; Zaremba et al., 2021). Nevertheless, further robustness checks demonstrate that our results also hold for other maturities. The daily temperature data are obtained from the Global Historical Climatology Network daily (GHCNd) database.[5] GHCNd is a product of the National Oceanic and Atmospheric Administration and contains daily records from more than 100,000 stations worldwide. Concretely, we use three different indicators for robustness: *Temp Max*, *Temp Min* and *Temp Avg*,

TABLE 1 Sample countries.

#	Country	#	Country	#	Country	#	Country	#	Country
1.	Australia	8.	Finland	15.	Ireland	22.	Norway	29.	Switzerland
2.	Austria	9.	France	16.	Italy	23.	Poland	30.	United Kingdom
3.	Belgium	10.	Germany	17.	Japan	24.	Portugal	31.	United States
4.	Canada	11.	Greece	18.	Korea	25.	Singapore		
5.	China	12.	Hungary	19.	Mexico	26.	South Africa		
6.	Czechia	13.	India	20.	Netherlands	27.	Spain		
7.	Denmark	14.	Indonesia	21.	New Zealand	28.	Sweden		

Note: This table displays the country bond markets that are covered in the study.

denoting the maximum, minimum and average daily temperature, respectively. The use of the level of daily temperature is informed by Kamstra et al. (2003) and Cao and Wei (2005a). However, as a robustness check, we also test our hypotheses using a detrended temperature variable. This database has been used in several prior studies, including Antweiler et al. (2001), Jacobsen and Marquering (2008) and Zinman and Zitzewitz (2016). Following Hirshleifer and Shumway (2003), the meteorological data are collected from the stations closest to the major local security exchange location. The temperature is expressed in degrees Fahrenheit.

Macroeconomic variables, encompassing the annual GDP growth rate (*GDP*), the inflation rate (*Inflation*) and the unemployment rate (*Unemployment*), are gathered from Global Financial Data.[6] The annual GDP growth rate approximates business-cycle fluctuations, and the inflation rate captures macroeconomic instabilities. Also, unemployment-related news carries information contents about a) future interest rates, b) equity risk premium and c) corporate earnings and dividends (Boyd et al., 2005). In this vein, Boyd et al. (2005) find that bond returns positively respond to unanticipated increases in unemployment in expansions, albeit not in contractions. Moreover, prior studies have shown that macroeconomic factors can be important influences on sovereign bond attributes. For instance, Cantor and Packer (1996) and Apergis (2015) find that GDP growth, inflation and the unemployment rate play an important role in determining sovereign credit ratings. Beirne and Fratzscher (2013) provide evidence that sovereign bond yield spreads can be explained by real GDP growth. Huang et al. (2015) document a significantly positive relationship between sovereign bond yields and the inflation rate. This suggests that government bond nominal yields should, at the very least, enable investors to offset the inflation effect (Kumar & Baldacci, 2010).

Furthermore, consistent with previous work on sovereign bonds (e.g., Boudoukh et al., 2021; Dufrénot et al., 2016; Oliveira et al., 2012; Zaremba et al., 2021; Zaremba et al., 2021), we control for bond-specific characteristics, namely, convexity (*Convexity*), duration (*Duration*), market value (*Market Value*) and sovereign ratings (*Rating*), sourced from Datastream. The final sample consists of panel data of 225,390 bond-day (or country-day) observations; however, due to missing data, the usable ones vary according to the regression specification. A detailed synthesis of the major variables and their explanations, measurements and sources is provided in Table A1 (see Supporting Information Appendix).

3.2 | Regression models

To explore the influence of temperature on sovereign bond returns, we rely on the following model and its nested variants:

$$R_{i,t} = \beta_0 + \beta_1 Temp_{i,t} + \sum_{j=2}^{n} \beta_j X_{j,i,t} + \delta_i + \varepsilon_{i,t}. \tag{1}$$

In Equation (1), the dependent variable is the daily sovereign bond return, $R_{i,t}$. To assume away all the issues associated with foreign exchange rates and risk, we follow Fama and French (2012, 2017) and express the market data in US dollars. The primary explanatory variable, $Temp_{i,t}$, is one of the three above-mentioned measures of daily temperature. $X_{i,t}$ represents a vector of control variables (bond characteristics, macroeconomic variables, year dummies, time trend and weekday dummies). For instance, the inclusion of the macroeconomic variables seeks to mitigate an omitted variable bias, which would arise if our temperature variables were correlated with the GDP growth rate or the stance of a business cycle. Equipped with this rationale, our methodology allows us to integrate the indirect link between sovereign bond valuation and temperature through either revised expectations of the GDP growth rate or the stance of the business cycle. This implies that the effects of temperature changes on sovereign bond returns are unrelated to the country's past economic performance. Thus, temperature shifts can create either investor behavioral motives (apathy/depression or aggression) or the expectation of quadratic losses to the economy and financial markets provoked by climate change-caused natural disasters. To avoid a look-ahead bias, macroeconomic variables are lagged by 3 months.

Our panel data models are estimated using the fixed-effects method. This estimation method assures that the examined temperature effect does not derive from cross-country structural variation. Fixed effects seek to account for unobserved heterogeneity in the responses of sovereign bond returns across countries, such as time-invariant factors. One source of such heterogeneity may reflect different investor beliefs about future sovereign bond returns in both developed and emerging market countries. In this sense, Li (2021) finds that emerging market bonds are treated by investors as risky assets, countering the widely held assumption that sovereign bonds can be regarded as vehicles of risk-free investment. The random disturbance term, $u_{i,t}$, can be decomposed into two components—according to $u_{i,t} = \delta_i + \varepsilon_{i,t}$. The first component, δ_i, is the time-invariant bond-specific (or country-specific) effect that reflects the heterogeneity of sovereign bond markets and local climate conditions. The second component, $\varepsilon_{i,t}$, is the idiosyncratic error term, assumed independently and identically distributed with a zero mean and standard deviation σ_ε.

An advantage of the fixed-effects estimation method relative to the random-effects estimator is that it does not restrict the correlations between the unobserved country fixed effects and the observed explanatory variables to zero. Moreover, the fixed-effects estimation method is more appropriate when the sample constitutes a "large" share of the population (Gelman, 2005; Green & Tukey, 1960). Our extensive panel of country-day observations can be deemed to meet this criterion. Moreover, the ensuing degree of freedom loss is not significant. To alleviate any remaining concerns about the fixed-effects estimation method, we also use the random-effects and pooled ordinary least squares (OLS) estimators. These estimation methods are justified, summarized and scrutinized in the Table A3, in the Supporting Information Appendix. Importantly, we show that the results are qualitatively unchanged when using random effects or pooled OLS estimation methods.

Further, the existing literature suggests that the relation between returns on financial market investments and temperature shifts is not necessarily linear, provided that natural disasters caused by climate change are associated with quadratic losses. Investors' decision to shift from fixed to variable income securities emanates from the expectation of quadratic losses caused by natural disasters. More generally, the responses of financial returns to temperature increases and decreases are notoriously asymmetric. Equipped with this evidence, we also consider a quadratic relation between sovereign bond returns and our temperature variables, as outlined in Equation (2):

$$R_{i,t} = \beta_0 + \beta_1 Temp_{i,t} + \beta_2 Temp_{i,t}^2 + \sum_{j=3}^{n} \beta_j X_{j,i,t} + \delta_i + \varepsilon_{i,t}. \quad (2)$$

Our methodology is also informed by the Chicago Mercantile Exchange's (CME) weather derivatives market. In this market, the prices of weather derivatives contracts are earmarked to temperature/weather outcomes. The payoff of a standard temperature derivative contract, traded on CME, is determined by either a HDD or a CDD. It is calculated in a location i at time t as $CDD_{i,t} = MAX\{Temp_{i,t} - 65, 0\}$ and $HDD_{i,t} = MAX\{65 - Temp_{i,t}, 0\}$, respectively. If the temperature is above the threshold of 65°F, $CDD_{i,t} > 0$ and $HDD_{i,t} = 0$. This signals a hot temperature shock (as cooling is required) and no cold temperature shock (since no heating is required). If, however, the temperature is below the threshold of 65°F, then $HDD_{i,t} > 0$ and $CDD_{i,t} = 0$. This signals a cold temperature shock, as heating is required. $HDD_{i,t}$ and $CDD_{i,t}$, akin to the payoff of a temperature derivative contract, are entailed in Equation (3) in lieu of our temperature variables:

$$R_{i,t} = \gamma_0 + \gamma_1 DD_{i,t} + \sum_{j=2}^{n} \gamma_j X_{j,i,t} + \delta_i + \varepsilon_{i,t}, \tag{3}$$

where $DD_{i,t}$ is either $HDD_{i,t}$ or $CDD_{i,t}$.

Finally, Equations (1–3) also incorporate year dummies. Alternatively, in other specifications, we include a time trend. The use of year dummies and the time trend ensures that our results are not driven by either the structural decrease in bond yields over the last decades or global warming.[7] Moreover, weekday dummies allow controlling for potential daily seasonality in bond behavior (Chiah & Zhong, 2019; Zaremba et al., 2021).

Equations (1–3) allow testing for the three hypotheses. H1 implies a positive relationship between temperature shifts and sovereign bond returns, so $\beta_1 > 0$. H2 implies a U-shaped relation, hence, $\beta_1 < 0$ and $\beta_2 > 0$. H3 implies that both hot and cold temperature shocks lead to an increase in sovereign bond returns; this implies $\gamma_1 > 0$.

3.3 | Descriptive statistics

Table 2 exhibits descriptive statistics on the variables employed in the baseline regression analysis. The mean daily bond returns range from 0.02% (2-year bonds) to 0.03% (5-, 10-, 20- and 30-year bonds). Statistics on bond convexity, duration and market value align with previous studies (e.g., Zaremba et al., 2021). Moreover, Table 2 shows an average daily temperature (*Temp Avg*) of about 59°F and an average maximum daily temperature (*Temp Max*) of about 62°F; this is far above the average minimum daily temperature (*Temp Min*), which equals almost 49°F.

Furthermore, we examine the variation over time in the country-specific sovereign bond returns. Specifically, Figure 1 illustrates the accumulated sovereign bond returns, calculated in relation to the base value of 100 assigned to the first available observation for a given country. The accumulated sovereign bond return indicates the value of the investment in the given country's sovereign bond relative to the base value of 100. Ireland, France and the UK are the countries where the investment value of sovereign bonds experienced periods of significant growth. On the other hand, the investment value in Indonesia, India and Korea's sovereign bonds remained flat over the sample period.

4 | EMPIRICAL FINDINGS

4.1 | The linear relation between bond returns and temperature

Table 3 reports the results from fixed-effects regressions estimating the influence of temperature on sovereign bond returns. The dependent variable is the country *i*'s sovereign 10-year bond return on day *t*. The key regressors are *Temp Max* (columns 1 and 2), *Temp Min* (columns 3 and 4) and *Temp Avg* (columns 5 and 6). In columns 1, 3 and 5, year dummies are included in the regression model, whereas in columns 2, 4 and 6, year dummies are replaced by a year trend. Following Abadie et al. (2017), Imbens and Kolesár (2016) and Petersen (2009), we use standard errors clustered by country; these are robust to within-country serial correlation and heteroskedasticity. Standard errors are shown in parentheses beneath the regression coefficients.

In general, the regression results match our theoretical conjectures. Air temperature positively influences government bond returns. The coefficients on the temperature variables are significant at the 1% level across all specifications and temperature measurement choices. Furthermore, the relationship is not explained by other control variables, including bond characteristics, macroeconomic situations, time trends or seasonal patterns. Notably, the

TABLE 2 Descriptive statistics.

	N	Mean	Std.	Min.	Max.	P25	Median	P75	Skewness	Kurtosis
Panel A: Temperature variables										
Temp Max	272,779	62.0205	18.4302	−80	116	49	63	76	−0.1822	2.5347
Temp Min	225,622	49.3852	14.9836	−29	94	39	50	59	−0.1413	2.9956
Temp Avg	234,003	58.5752	16.5024	−13	104	47	59	71	−0.1486	2.4877
CDD Max	329,344	5.0741	8.5781	0	51	0	0	8	1.7279	5.2023
CDD Min	329,344	0.7981	2.8491	0	29	0	0	0	3.9537	19.0364
CDD Avg	329344	2.8212	6.0834	0	39	0	0	0	2.2149	7.044
HDD Max	329,344	7.5418	11.5099	0	145	0	0	13	1.5717	4.8689
HDD Min	329,344	11.4952	13.4143	0	94	0	7	21	1.0464	3.449
HDD Avg	329,344	7.3862	11.104	0	78	0	0	13	1.5278	4.616
SAD	329,344	0.8996	1.6067	−2.8705	7.2858	0	0	1.6737	1.3859	4.6859
Panel B: Sovereign bonds variables										
Return 2Y	202,512	0.0002	0.0066	−0.1762	0.1836	−0.003	0.0002	0.0034	0.0817	16.7998
Return 5Y	225,390	0.0003	0.0071	−0.1206	0.3247	−0.0032	0.0002	0.0038	0.4016	32.1677
Return 10Y	220,043	0.0003	0.0082	−0.2478	0.4176	−0.0037	0.0002	0.0043	0.7632	70.1934
Return 20Y	67,997	0.0003	0.0086	−0.1013	0.5253	−0.0039	0.0003	0.0046	3.3022	216.8734
Return 30Y	107,907	0.0003	0.0096	−0.174	0.1866	−0.0045	0.0003	0.0053	−0.1042	11.8213
Convexity 2Y	202,485	4.5338	1.4444	0.0391	14.7141	3.7726	4.5461	5.2517	1.2554	9.3542
Convexity 5Y	225,361	20.405	4.4691	1	52.7424	17.2504	20.2213	23.295	0.4109	4.281
Convexity 10Y	220,012	62.9983	17.8111	1	120.4196	49.7628	61.4206	73.7091	0.4077	2.7191
Convexity 20Y	67,986	155.6515	67.4099	1	397.2485	103.5244	142.1946	194.4613	0.8677	3.5625
Convexity 30Y	107,888	268.8173	146.8795	1	965.9202	150.4079	247.8213	359.5272	0.9645	4.0051
Duration 2Y	202,485	1.721	0.2844	0.0338	2.6824	1.5905	1.7855	1.9084	−1.0205	4.3821
Duration 5Y	225,361	4.1898	0.4089	1.8402	5.7154	3.9276	4.2182	4.478	−0.4482	3.6276

(Continues)

TABLE 2 (Continued)

Panel B: Sovereign bonds variables										
Duration 10Y	220,012	7.7261	0.9683	3.2096	10.509	7.0395	7.709	8.3645	0.0413	2.681
Duration 20Y	67,986	12.2437	2.4452	6.3055	19.4727	10.3094	12.0083	13.8731	0.3953	2.7362
Duration 30Y	107,888	15.9694	4.2079	6.568	30.526	12.5508	15.9009	19.0387	0.2975	2.6536
Market value 2Y	202,485	10.2244	73.7344	0.0151	1.91E + 04	2.3336	7.0965	14.0734	252.3294	6.49E + 04
Market value 5Y	225,361	0	0	0	0.0001	0	0	0	2.3852	10.9891
Market value 10Y	220,012	9.3173	10.0074	0.0014	225.4143	2.9504	6.7129	12.1643	4.1892	49.8689
Market value 20Y	67,986	12.0782	13.4177	0.008	64.4536	2.9128	6.2355	15.9094	1.558	4.58
Market value 30Y	107,888	12.7703	14.9309	0.075	1,907.0798	5.3519	10.3807	17.7984	72.8914	9,076.408
Rating	286,293	3.7926	3.6673	1	21.3333	1	2	6	1.3618	4.1483
Panel C: Macroeconomic variables										
GDP	327,540	3.5979	11.6119	−71.3386	334.2848	1.3545	2.9358	5.0053	21.7645	602.7863
Inflation	318,720	6.2898	30.1302	−6.5878	1,366.6667	1.4726	2.7849	5.8278	31.2221	1,145.7184
Unemployment	307,056	7.5594	9.2938	0.1399	279	4.1	6.3	8.9	21.4413	619.079

Note: This table shows descriptive statistics on all bond- and temperature-related variables that are used in our analysis. The set of variables include country *i*'s sovereign 2-, 5-, 10-, 20- and 30-year bond returns on day *t*. *Temp Max*, *Temp Min* and *Temp Avg* are defined as the daily maximum, minimum and average temperature measurements for country *i* on day *t*, respectively. *CDD Max*, *CDD Min and CDD Avg* are the daily maximum, minimum and average cooling degree days for country *i* on day *t*, respectively; they are calculated as $CDD_{i,t} = MAX\{Temp_{i,t} - 65, 0\}$. *HDD Max*, *HDD Min* and *HDD Avg* are the daily maximum, minimum and average heating degree days for country *i* on day *t*, respectively; they are calculated as $HDD_{i,t} = MAX\{65 - Temp_{i,t}, 0\}$. SAD is the seasonal affective disorder (the length of night in hours relative to the average night length of 12 h in the fall and winter months) in country *i* on day *t*, computed using the methodology of Kamstra et al. (2003). *Convexity* and *Duration* are the average adjusted convexity and duration of the bond market index on day *t*−1, respectively; *Market Value* is the natural logarithm of the market value (in US dollars) on day *t*−1 of the government bond market portfolio. *Rating* is the rating-based credit risk; it is computed as the average score on day *t*−1 from Moody's, S&P and Fitch of the numerical sovereign ratings of the government bonds in the index. The variables *GDP*, *Inflation* and *Unemployment* are the GDP growth rate, the inflation rate and the unemployment rate, respectively. The sample period runs from 1 January 1980 to 18 September 2020. The cross-section comprises 31 countries.

TABLE 3 Temperature and sovereign bond returns: Main regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
Temp Max	0.035***	0.034***				
	(0.011)	(0.011)				
Temp Min			0.050***	0.047***		
			(0.013)	(0.013)		
Temp Avg					0.046***	0.044***
					(0.011)	(0.011)
Convexity	−0.397***	−0.154	−0.462***	−0.197	−0.261**	−0.070
	(0.110)	(0.140)	(0.141)	(0.181)	(0.095)	(0.137)
Duration	4.960**	0.762	6.200**	1.430	2.810*	−0.328
	(1.890)	(2.350)	(2.350)	(3.000)	(1.640)	(2.340)
Market value	−0.019	−0.020	−0.014	−0.031	−0.015	−0.021
	(0.032)	(0.031)	(0.050)	(0.048)	(0.045)	(0.046)
GDP	0.237	0.139	0.240	0.108	0.289	0.156
	(0.217)	(0.188)	(0.237)	(0.217)	(0.270)	(0.244)
Inflation	0.449***	0.259**	0.478**	0.218	0.471***	0.324**
	(0.136)	(0.114)	(0.197)	(0.143)	(0.132)	(0.150)
Unemployment	0.296	0.214	0.266	0.187	0.386*	0.248
	(0.200)	(0.200)	(0.225)	(0.233)	(0.200)	(0.206)
Rating	−0.227	−0.239	−0.282	−0.337	−0.380	−0.344
	(0.457)	(0.426)	(0.558)	(0.540)	(0.460)	(0.419)
Year trend		0.110*		0.118		0.073
		(0.059)		(0.076)		(0.066)
Weekday dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	No	Yes	No	Yes	No
Obs.	183,934	183,934	151,646	151,646	145,294	145,294
R^2	0.003	0.001	0.003	0.001	0.002	0.001

Note: This table reports the results from fixed-effects regressions estimating the effect of temperature on sovereign bond returns. The dependent variable is country *i*'s sovereign 10-year bond return on day *t*. *Temp Max*, *Temp Min* and *Temp Avg* are the daily maximum, minimum and average temperature measurements for country *i* on day *t*, respectively. *Convexity* and *Duration* are the average adjusted convexity and duration of the bond market index on day *t*−1, respectively; *Market Value* is the natural logarithm of the market value (in US dollars) on day *t*−1 of the government bond market portfolio. *Rating* is the rating-based credit risk; it is computed as the average score on day *t*−1 from Moody's, S&P and Fitch of the numerical sovereign ratings of the government bonds in the index. The variables *GDP*, *Inflation* and *Unemployment* are the GDP growth rate, the inflation rate and the unemployment rate, respectively. All regressions include weekday dummies. Year dummies are included in columns 1, 3 and 5 in the regression model; they are replaced by a year trend in columns 2, 4 and 6. We use standard errors clustered by country, which are robust to within-country serial correlation and heteroskedasticity. Standard errors are shown in parentheses beneath the regression coefficients. To improve the readability of the tables, we multiply all the coefficients and standard errors by 10,000. Obs. and R^2 denote the number of observations and the coefficient of determination, respectively. The sample period runs from 1 January 1980 to 18 September 2020. The cross-section comprises 31 countries.

***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

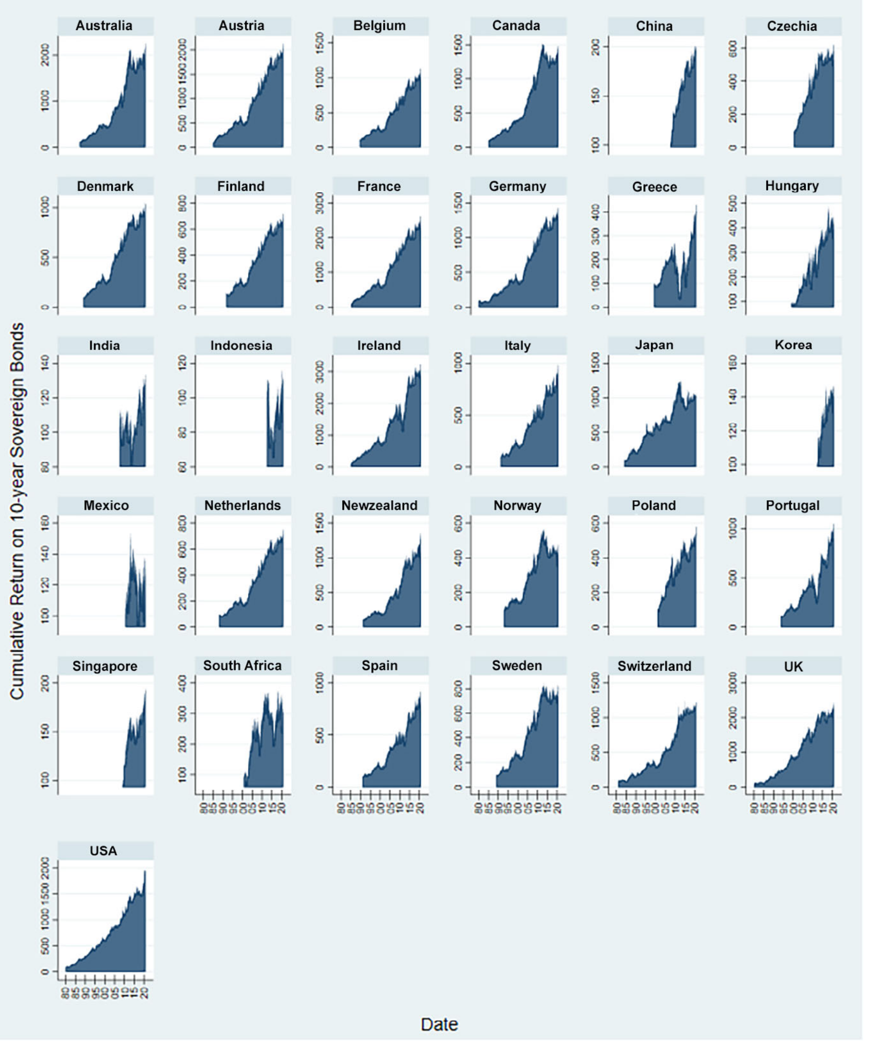

FIGURE 1 Accumulated returns on 10-year sovereign bonds. This figure visualizes the variation over time in the accumulated returns on 10-year sovereign bonds. The accumulated return has a base value of 100. Values >100 indicate an increase in the investment value of a sovereign bond, whereas values <100 indicate that the investment value has declined relative to the base value of 100. The sample period runs from 1 January 1980 to 18 September 2020. The cross section comprises 31 countries. [Color figure can be viewed at wileyonlinelibrary.com]

positive effect of temperature is also economically important. The regression coefficients range from 0.034 to 0.050. This implies that a temperature surge by 10°F raises the daily bond return between 0.34 and 0.5 basis points. Given the mean daily 10-year bond return of 0.03% (as seen in Table 2), this implies an 11%–17% increase over the long-run sample average.

These findings are consistent with prior studies that attribute the effect of weather conditions on financial market investments to the established macroeconomic channels (i.e., patent obsolescence, labor productivity and capital quality) (Donadelli et al., 2021); the findings are also in line with prior studies' examinations of investors' mood by showing that their apathy—and thus risk aversion—increases with temperature (cf., Cao & Wei, 2005a; Chang et al., 2008). Notably, our results are closely related to those of Cao and Wei (2005a), who show that the higher the temperature, the lower the stock returns—and vice versa. However, our results disagree with Bassi et al. (2013), who show that good weather (i.e., higher temperature) induces more risk-taking. As we previously noted, one plausible interpretation of Table 3 is that a higher temperature significantly affects investors' mood, which results in more apathy that impedes risk-taking and prompts investors to shift their investments from stocks to government bonds. However, lower daily temperatures lead to more aggression; this leads to an increase in risk-taking and discourages people from investing in government bonds. Overall, the results summarized in Table 3 provide evidence that supports hypothesis H1.

4.2 | The quadratic relation between bond returns and temperature

The assumption of a linear relationship between bond returns and temperature, maintained in Section 4.1, neglects the possible presence of both non-linearities and asymmetries. As a remedy, we estimate a battery of regression models that allow for a quadratic relationship between sovereign bond returns and temperature. The results are visualized in Table 4.

The results indicate the presence of a significant quadratic temperature effect on sovereign bond returns. In particular, $Temp^2_{i,t}$ exerts a positive and significant impact on sovereign bond returns. However, the linear effect is significant only for *Temp Avg*. For the temperature variables *Temp Max* and *Temp Min*, the linear effect of $Temp_{i,t}$ is negative—albeit insignificant. Hence, the effect of a unitary temperature change on the dependent variable is no longer constant—supporting hypothesis H2. Rather, it depends on the value the temperature variable takes on. The assumption of a quadratic relation between sovereign bond returns and temperature enables us to determine the threshold temperature value.

We note that the temperature effect on sovereign returns is given by the first partial derivative of $R_{i,t}$, with regard to $Temp_{i,t}$: $\frac{\partial R_{i,t}}{\partial Temp_{i,t}} = \beta_1 + 2\beta_2 \times Temp_{i,t} = 0$. Operating yields $Temp^*_{i,t} = -\beta_1/2\beta_2$. The estimated threshold temperature ranges from 25.38°F (−3.68°C) to 50.33°F (10.18°C). [8] Thus, if the temperature is <25.39°F, a unitary temperature increase exerts a negative effect on sovereign bond returns. If the temperature is >50.33°F, a unitary temperature increase instigates a positive effect on the sovereign bond returns. If the temperature ranges between 25.38°F and 50.33°F, the effect can be positive, negative or 0.[9] For instance, if $Temp_{i,t} = 58.58°F$ (the mean of *Temp Avg*), then, $\frac{\partial R_{i,t}}{\partial Temp_{i,t}} = \beta_1 + 2\beta_2 \times Temp_{i,t} = -0.134 + 2 \times 0.0016 \times 58.58 = 0.0535$. Thus, a 10°F temperature rise is followed by an increase in sovereign bond returns by 0.535 basis points. It is worth noting that the partial derivative falls within the range of coefficient estimates that are discussed in Section 4.1 and reported in Table 3.

4.3 | Temperature, sovereign bond returns and SAD

The temperature effects on sovereign bond returns (documented in Sections 4.1 and 4.2) can be attributed to two paradigms: macroeconomic and behavioral. The macroeconomic paradigm implies that a temperature shock can trigger a decline in R&D expenditure—and thus the GDP growth rate—through at least three channels: patent obsolescence, labor productivity and capital quality (Donadelli et al., 2021). This, in turn, leads to a lower rate of return on stock market investments and a higher rate of return on sovereign bonds. On the other hand, the behavioral paradigm is informed by psychological theories, according to which low temperature is associated with increased risk-taking and, therefore, higher returns on risky investments; whereas higher temperature leads to either aggression or apathy. Thus, temperature increases are more likely to lead to a higher degree of risk aversion than temperature decreases; because of this, investors will tend to switch from equity to debt financial instruments—with particular emphasis on sovereign bonds.

It is worth mentioning that aggression may not be the only behavioral outcome induced by low temperatures. In fact, low temperatures can have overlapping information contents with the SAD—investigated by Kamstra et al. (2003). SAD is a clinical condition that can affect investors during seasons of relatively fewer daylight hours. Kamstra et al. (2003) argue that SAD is systematically linked with individuals' moods. Specifically, individuals are deprived of

TABLE 4 Temperature and sovereign bond returns: Quadratic regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
Temp Max	−0.089	−0.090				
	(0.062)	(0.061)				
Temp Max^2	0.0011**	0.0011**				
	(0.0005)	(0.0005)				
Temp Min			−0.066	−0.082		
			(0.063)	(0.063)		
Temp Min^2			0.0013*	0.0015*		
			(0.0007)	(0.0008)		
Temp Avg					−0.134**	−0.151**
					(0.056)	(0.059)
Temp Avg^2					0.0016***	0.0015***
					(0.0005)	(0.0006)
Convexity	−0.394***	−0.152	−0.461***	−0.195	−0.258**	−0.068
	(0.110)	(0.140)	(0.141)	(0.180)	(0.095)	(0.137)
Duration	4.910**	0.730	6.170**	1.410	2.760	−0.369
	(1.890)	(2.350)	(2.350)	(3.010)	(1.640)	(2.340)
Market value	−0.019	−0.020	−0.014	−0.030	−0.016	−0.021
	(0.032)	(0.031)	(0.050)	(0.048)	(0.045)	(0.046)
GDP	0.237	0.140	0.240	0.110	0.290	0.160
	(0.217)	(0.188)	(0.237)	(0.217)	(0.270)	(0.244)
Inflation	0.450***	0.261**	0.480**	0.221	0.474***	0.325**
	(0.135)	(0.114)	(0.197)	(0.142)	(0.130)	(0.150)
Unemployment	0.296	0.213	0.267	0.186	0.385*	0.246
	(0.200)	(0.200)	(0.225)	(0.233)	(0.201)	(0.206)
Rating	−0.229	−0.240	−0.285	−0.337	−0.384	−0.347
	(0.457)	(0.427)	(0.558)	(0.540)	(0.460)	(0.419)
Year trend		0.110*		0.118		0.074
		(0.059)		(0.076)		(0.066)
Weekday dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	No	Yes	No	Yes	No
Obs.	183,934	183,934	151,646	151,646	145,294	145,294
R^2	0.003	0.001	0.003	0.001	0.003	0.001

Note: This table reports the results from fixed-effects regressions estimating the effect of temperature on sovereign bond returns. The dependent variable is country *i*'s sovereign 10-year bond return on day *t*. *Temp Max*, *Temp Min* and *Temp Avg* are the daily maximum, minimum and average temperature measurements for country *i* on day *t*, respectively. *Convexity* and *Duration* are the average adjusted convexity and duration of the bond market index on day *t*−1, respectively; *Market Value* is the natural logarithm of the market value (in US dollars) on day *t*−1 of the government bond market portfolio. *Rating* is the rating-based credit risk, computed as the average score on day *t*−1 from Moody's, S&P and Fitch of the numerical sovereign ratings of the government bonds in the index. The variables *GDP*, *Inflation* and *Unemployment* are the GDP growth rate, the inflation rate and the unemployment rate, respectively. All regressions include weekday dummies. Year dummies are included in columns 1, 3 and 5 in the regression model; they are replaced by a year trend in columns 2, 4 and 6. We use standard errors clustered by

(Continues)

TABLE 4 (Continued)

country, which are robust to within-country serial correlation and heteroskedasticity. Standard errors are shown in parentheses beneath the regression coefficients. To improve the readability of the tables, we multiply all the coefficients and standard errors by 10,000. Obs. and R^2 denotes the number of observations and the coefficient of determination, respectively. The sample period runs from 1 January 1980 to 18 September 2020. The cross-section comprises 31 countries.
***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

daylight during fall and winter, resulting in depression and lower risk-taking. In this study, we argue that in periods of longer daylight hours, individuals prefer to invest in sovereign bonds. Since the fall and winter periods are correlated with lower temperatures, SAD shares information contents with temperature. It is, therefore, not surprising that SAD is strongly negatively correlated with temperature. In an unreported analysis, we find that the coefficients of correlation range between SAD and temperature range from −0.70 to −0.63. Whether individuals are willing to take or avert risks depends on whether they become more aggressive or depressed in periods of low temperature and limited daylight.

We follow Kamstra et al. (2003) to construct the SAD measure, which measures the length of night in the fall and winter periods relative to the mean annual length of 12 h in country *i* on day *t* as follows:

$$SAD_t = \begin{Bmatrix} H_t - 12 \text{ if the trading day is in the fall or winter} \\ 0 \text{ otherwise} \end{Bmatrix}, \tag{4}$$

where,

$$H_t = \begin{Bmatrix} 24 - 7.72 \times \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right) \times \tan(\lambda_t)\right] \\ 7.72 \times \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right) \times \tan(\lambda_t)\right] \end{Bmatrix}, \tag{5}$$

where the upper element of H_t (the length of night in country *i* on day *t*) is the number of hours of a night in the northern hemisphere, the lower element is the number of hours of a night in the southern hemisphere and λ_t is the sun's declination angle at latitude δ:

$$\lambda_t = 0.4102 \times \sin\left[\left(\frac{2\pi}{365}\right)(julian_t - 80.25)\right], \tag{6}$$

where $julian_t$ is a variable that takes values from 1 to 365 (366 in a leap year). It represents the number of days in the year. The above arguments indicate a negative effect of SAD on sovereign bond returns. The ensuing regression model that evaluates the effect of SAD (as well as the effect of temperature) on sovereign bond returns is given by:

$$R_{i,t} = \beta_0 + \beta_1 Temp_{i,t} + \lambda \times SAD_{i,t} + \sum_{j=2}^{n} \beta_j X_{j,i,t} + \delta_i + \varepsilon_{i,t}. \tag{7}$$

The results are summarized in Table 5.

Table 5 shows that SAD exerts both a negative (as expected) and statistically significant effect on sovereign bond returns (see columns 1 and 2). A 1 h increase in the length of night in the fall or winter, relative to the average length of a night of 12 h, is associated with a decline in sovereign bond returns between 0.180 and 0.207 basis points. However, when included jointly with the temperature variables (columns 3–8), the effect of SAD ceases to be significant. By contrast, the effects of the temperature variables (*Temp Max*, *Temp Min* and *Temp Avg*) remain both positive and significant. The results indicate that a 10°F temperature rise commands an increase in sovereign bond returns between 0.35 and 0.50 basis points; this is in line with our baseline results. Therefore, this robustness exercise appears to suggest that the investor's transactions in sovereign bond markets are mainly motivated by either temperature-induced changes in the

TABLE 5 Temperature, sovereign bond returns and seasonal affective disorder (SAD).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SAD	−0.180***	−0.207***	0.068	0.017	−0.037	−0.092	0.138	0.089
	(0.032)	(0.031)	(0.103)	(0.098)	(0.122)	(0.116)	(0.093)	(0.088)
Temp Max			0.039**	0.035**				
			(0.016)	(0.016)				
Temp Min					0.047**	0.041***		
					(0.019)	(0.019)		
Temp Avg							0.055***	0.050***
							(0.016)	(0.016)
Convexity	−0.487***	−0.303**	−0.398***	−0.154	−0.462***	−0.196	−0.263**	−0.071
	(0.162)	(0.149)	(0.110)	(0.140)	(0.141)	(0.180)	(0.095)	(0.137)
Duration	6.810**	3.410	4.980**	0.766	6.200**	1.420	2.840*	−0.313
	(2.780)	(2.590)	(1.890)	(2.340)	(2.340)	(3.000)	(1.650)	(2.350)
Market value	-0.042	-0.038	−0.019	−0.020	−0.014	−0.031	−0.016	−0.021
	(0.039)	(0.037)	(0.032)	(0.031)	(0.050)	(0.048)	(0.045)	(0.046)
GDP	0.086	0.057	0.238	0.139	0.240	0.108	0.290	0.156
	(0.105)	(0.099)	(0.217)	(0.188)	(0.237)	(0.217)	(0.270)	(0.244)
Inflation	0.482***	0.354***	0.450***	0.259**	0.477**	0.216	0.474***	0.325**
	(0.092)	(0.102)	(0.136)	(0.114)	(0.196)	(0.142)	(0.131)	(0.150)
Unemployment	0.274	0.207	0.297	0.214	0.266	0.185	0.387*	0.249
	(0.187)	(0.176)	(0.200)	(0.200)	(0.226)	(0.233)	(0.200)	(0.206)
Rating	0.054	0.057	−0.227	−0.239	−0.282	−0.335	−0.381	−0.345
	(0.299)	(0.220)	(0.458)	(0.427)	(0.559)	(0.540)	(0.461)	(0.419)
Year trend		0.133**		0.110*		0.118		0.073
		(0.062)		(0.059)		(0.076)		(0.066)
Weekday dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	No	Yes	No	Yes	No	Yes	No
Obs.	215,461	215,461	183,934	183,934	151,646	151,646	145,294	145,294
R^2	0.003	0.001	0.003	0.001	0.003	0.001	0.002	0.001

Note: This table reports the results from fixed-effects regressions estimating the effect of temperature on sovereign bond returns. The dependent variable is country *i*'s sovereign 10-year bond return on day *t*. It is calculated following the methodology proposed by Kamstra et al. (2003). *Temp Max*, *Temp Min* and *Temp Avg* are the daily maximum, minimum and average temperature measurements for country *i* on day *t*,respectively. *Convexity* and *Duration* are the average adjusted convexity and duration of the bond market index on day *t*−1, respectively; *Market Value* is the natural logarithm of the market value (in US dollars) on day *t*−1 of the government bond market portfolio. *Rating* is the rating-based credit risk; it is computed as the average score on day *t*−1 from Moody's, S&P and Fitch of the numerical sovereign ratings of the government bonds in the index. The variables *GDP*, *Inflation* and *Unemployment* are the GDP growth rate, the inflation rate and the unemployment rate, respectively. All regressions include weekday dummies. Year dummies are included in columns 1, 3 and 5 in the regression model; they are replaced by a year trend in columns 2, 4 and 6. We use standard errors clustered by country, which are robust to within-country serial correlation and heteroskedasticity. Standard errors are shown in parentheses beneath the regression coefficients. To improve the readability of the tables, we multiply all the coefficients and standard errors by 10,000. Obs. and R^2 denote the number of observations and the coefficient of determination, respectively. The sample period runs from 1 January 1980 to 18 September 2020. The cross-section comprises 31 countries.

***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

apathy of investors or their knowledge of macroeconomic channels (e.g., patent obsolescence rate, labor productivity or capital quality). Interestingly, the results in Table 5 indicate that while depression is not statistically unimportant, it does not seem to command a critical mass of investors in the sovereign bond market. Importantly, the results support hypothesis H1, which predicts a positive association between temperatures and sovereign bond returns.

As a further exercise, we also incorporate SAD into the regression model that envisages a quadratic relation between sovereign bond returns and our temperature variables. The resulting regression model that evaluates the effect of SAD (as well as the linear and quadratic effects of temperature) on sovereign bond returns is given by:

$$R_{i,t} = \beta_0 + \beta_1 Temp_{i,t} + \beta_2 Temp_{i,t}^2 + \lambda \times SAD_{i,t} + \sum_{j=3}^{n} \beta_j X_{j,i,t} + \delta_i + \varepsilon_{i,t}. \tag{8}$$

The results are visualized in Table 6.

Table 6 shows that, when compared with Table 4, SAD does not appear to alter the quadratic temperature effect on sovereign bond returns. Again, similar to the results in Table 5, depression during periods of low temperatures and limited daylight is not the dominant driver of sovereign bond returns. More interestingly, we find that the estimate of β_2 remains positive and significant, which validates Hypothesis H2. Thus, Table 6 suggests that in periods of low temperature and limited daylight, investors in sovereign bonds are likely to price in the probability of quadratic losses caused by natural disasters. This conforms to the macroeconomic channels that underly the temperature-sovereign bond returns nexus.

To sum up, we find that SAD negatively influences sovereign bond returns, in consonance with psychological theories. This result posits that individuals deprived of daylight are more likely to suffer from depression, resulting in lower risk-taking in financial markets. This also means that investors will be willing to accept a lower rate of return on sovereign bonds. Nevertheless, this effect becomes significantly weaker when temperatures are controlled in both linear and quadratic ways.

4.4 | The relation between hot and cold temperature shocks and sovereign bond returns

The energy-demand-based narrative implies that both hot and cold temperature shocks are associated with higher energy and hedging costs. As a company's operational costs rise, it becomes a more leveraged and, thus, riskier vehicle of investment. In consequence, investors may decide to rebalance their portfolios by taking short positions in relatively risky assets and going long in relatively safe assets. Therefore, if the energy-demand channel drives the relation between temperature shocks and sovereign stock returns, we expect γ_1 to be significantly positive in Equation (3), following the discussion in Section 2. The results are summarized in Table 7.

The results in Table 7 are consistent with hypothesis H3, which postulates that hot temperature shocks command an increase in sovereign bond returns. The coefficient estimates are significant for the maximum and average CDD, albeit not for the minimum CDD. An unanticipated 10°F temperature rise instigates an increase in sovereign bond returns between 0.76 and 1.04 basis points; this is consistent with the energy demand-based view. However, to ascertain if unexpected rises in energy demand induced by cold temperature shocks translate into higher sovereign bond returns, we also scrutinize the regression models that entail the HDD. The results are tabulated in Table 8.

Table 8 shows that hypothesis H3 does not receive support from the data. The estimate of γ_1 takes on a negative sign, which can be regarded as a substantial variation from the energy demand-based view. The coefficient estimates are significant for the minimum and average HDD, albeit not for the maximum HDD. The fact that hot temperature shocks increase bond returns whereas cold temperature shocks decrease returns is more consonant with the behavioral paradigm, which helps to underscore the role of temperature-induced apathy in the investor's financial decisions. Therefore, a cold temperature shock is associated with more aggression by investors, who become more willing to take risks while reducing their holdings of safer financial investments—such as bonds.

TABLE 6 Temperature, sovereign bond returns and seasonal affective disorder (SAD): Quadratic regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
SAD	−0.010	−0.049	−0.072	−0.132	0.050	−0.009
	(0.098)	(0.094)	(0.120)	(0.114)	(0.096)	(0.092)
Temp Max	−0.075	−0.097				
	(0.063)	(0.065)				
Temp Max^2	0.0009*	0.001**				
	(0.0005)	(0.005)				
Temp Min			−0.076	−0.100		
			(0.063)	(0.065)		
Temp Min^2			0.0013*	0.0015*		
			(0.0007)	(0.0008)		
Temp Avg					−0.125**	−0.152**
					(0.058)	(0.061)
Temp Avg^2					0.0016***	0.0018***
					(0.0005)	(0.0006)
Convexity	−0.394***	−0.152	−0.460***	−0.195	−0.259***	−0.068
	(0.110)	(0.140)	(0.141)	(0.180)	(0.095)	(0.137)
Duration	4.920***	0.719	6.160**	1.390	2.770	−0.370
	(0.189)	(2.350)	(0.235)	(3.000)	(1.640)	(2.340)
Market value	−0.019	−0.020	−0.013	−0.030	−0.016	−0.021
	(0.032)	(0.031)	(0.050)	(0.048)	(0.045)	(0.046)
GDP	0.237	0.140	0.239	0.109	0.291	0.160
	(0.217)	(0.188)	(0.237)	(0.217)	(0.270)	(0.244)
Inflation	0.450***	0.260**	0.479**	0.218	0.475***	0.325**
	(0.135)	(0.114)	(0.196)	(0.142)	(0.130)	(0.150)
Unemployment	0.296	0.212	0.265	0.184	0.385*	0.246
	(0.201)	(0.200)	(0.226)	(0.233)	(0.201)	(0.206)
Rating	−0.229	−0.240	−0.284	−0.335	−0.384	−0.347
	(0.457)	(0.426)	(0.559)	(0.540)	(0.460)	(0.419)
Year trend		0.110*		0.118		0.074
		(0.059)		(0.075)		(0.066)
Controls and weekday dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	No	Yes	No	Yes	No
Obs.	183,934	183,934	151,646	151,646	145,294	145,294
R^2	0.003	0.001	0.003	0.001	0.002	0.001

Note: This table reports the results from fixed-effects regressions estimating the effect of temperature on sovereign bond returns. The dependent variable is country *i*'s sovereign 10-year bond return on day *t*. It is calculated following the methodology proposed by Kamstra et al. (2003). *Temp Max*, *Temp Min* and *Temp Avg* are the daily maximum, minimum and average temperature measurements for country *i* on day *t*, respectively. *Convexity* and *Duration* are the average adjusted convexity and duration of the bond market index on day *t*−1, respectively; *Market Value* is the natural logarithm of the market value (in US dollars) on day *t*−1 of the government bond market portfolio. *Rating* is the rating-based credit risk; it is computed as the

(Continues)

TABLE 6 (Continued)

average score on day $t-1$ from Moody's, S&P and Fitch of the numerical sovereign ratings of the government bonds in the index. The variables *GDP, Inflation* and *Unemployment* are the GDP growth rate, the inflation rate and the unemployment rate, respectively. All regressions include weekday dummies. Year dummies are included in columns 1, 3 and 5 in the regression model; they are replaced by a year trend in columns 2, 4 and 6. We use standard errors clustered by country, which are robust to within-country serial correlation and heteroskedasticity. Standard errors are shown in parentheses beneath the regression coefficients. To improve the readability of the tables, we multiply all the coefficients and standard errors by 10,000. Obs. and R^2 denote the number of observations and the coefficient of determination, respectively. The sample period runs from 1 January 1980 to 18 September 2020. The cross-section comprises 31 countries.
***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

4.5 | Robustness checks

To ensure our findings' robustness, we supplement them with several robustness checks. For brevity, the results of these analyses are summarized here and reported in detail in the Supporting Information Appendix.

4.5.1 | Alternative bond maturities

Our baseline results in Table 3 relied on 10-year government bonds. In Table A2, in the Supporting Information Appendix, we repeat our baseline regressions on the subsamples of 2-, 5-, 20- and 30-year sovereign bonds (Panels A, B, C and D, respectively). We include year dummies (columns 1, 3 and 5) and a year trend (columns 2, 4 and 6) in our regressions. For the sake of brevity, coefficient estimates for control variables are not reported. All temperature-related coefficients are significantly positive at conventional levels; this corroborates our earlier results. In other words, our findings are not specific to any type of bond; they hold for the entire array of short- and long-term bonds. Notably, the regression coefficients are relatively higher for long-run bonds than for short-term bonds. This effect may be driven by a generally larger sensitivity of long-run bonds to changes in the external environment, which is dictated by their longer duration.

4.5.2 | Alternative regression frameworks

We also check whether our inferences remain unaffected if we re-estimate Equation (1) using alternative estimation methods. To be specific, we replaced the fixed effects with both random effects and panel OLS estimators. The random-effects estimator is recommended when the researcher is particularly interested in the population from which the sample is taken rather than unobserved country-specific characteristics—per se (Gelman, 2005; Searle et al., 2009, pp. 15–16). As a further robustness check, we employ the pooled OLS estimation method with no fixed or random effects. Following Wooldridge (2002, p. 150), the panel OLS estimator is consistent—insofar as it satisfies two conditions. First, the panel regression must fulfil the orthogonality condition implying $E\,(X'_{i,t} \times u_{i,t}) = 0$, where $X'_{i,t}$ is the row vector of the explanatory variables. Second, the model must meet the mild rank condition $(X'_{i,t} \times X_{i,t}) = K$; where K is the number of explanatory variables in the model. For the sake of brevity, coefficient estimates for control variables are not displayed. The results are displayed in Table A3, in the Supporting Information Appendix. The coefficients that are estimated by means of random effects (Panel A) and pooled OLS (Panel B) estimators qualitatively resemble those summarized in Table 3. In other words, our results do not depend on the model estimation approach and—therefore—remain qualitatively unaltered.

TABLE 7 Hot temperature shocks and sovereign bond returns.

	(1)	(2)	(3)	(4)	(5)	(6)
CDD Max	0.083**	0.076**				
	(0.022)	(0.023)				
CDD Min			0.009	0.004		
			(0.086)	(0.087)		
CDD Avg					0.096**	0.104***
					(0.036)	(0.038)
Convexity	−0.496***	−0.302**	−0.490***	−0.304**	−0.490*	−0.306**
	(0.164)	(0.150)	(0.163)	(0.150)	(0.164)	(0.150)
Duration	6.920**	3.400	6.880**	3.470	6.860**	3.470
	(2.810)	(2.610)	(2.780)	(2.600)	(2.800)	(2.610)
Market value	−0.042	−0.039	−0.043	−0.039	−0.043	−0.039
	(0.039)	(0.037)	(0.039)	(0.037)	(0.039)	(0.037)
GDP	0.084	0.056	0.086	0.058	0.085	0.058
	(0.104)	(0.099)	(0.104)	(0.099)	(0.104)	(0.098)
Inflation	0.471***	0.349**	0.486**	0.358***	0.488***	0.357**
	(0.094)	(0.104)	(0.092)	(0.102)	(0.091)	(0.101)
Unemployment	0.279	0.207	0.277	0.210	0.278	0.213
	(0.190)	(0.180)	(0.186)	(0.175)	(0.188)	(0.177)
Rating	0.058	0.073	0.053	0.057	0.050	0.052
	(0.297)	(0.220)	(0.299)	(0.220)	(0.298)	(0.217)
Year trend		0.133**		0.133**		0.134**
		(0.063)		(0.062)		(0.063)
Weekday dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	No	Yes	No	Yes	No
Obs.	215,461	215,461	215,461	215,461	215,461	215,461
R^2	0.003	0.001	0.003	0.001	0.003	0.001

Note: This table reports the results from fixed-effects regressions estimating the effect of temperature on sovereign bond returns. The dependent variable is country *i*'s sovereign 10-year bond return on day *t*. *CDD Max*, *CDD Min* and *CDD Avg* are the daily maximum, minimum and average cooling degree days for country *i* on day *t*, respectively; they are calculated as $CDD_{i,t} = MAX\{Temp_{i,t} - 65, 0\}$ and $HDD_{i,t} = MAX\{65 - Temp_{i,t}, 0\}$. *Convexity* and *Duration* are the average adjusted convexity and duration of the bond market index on day $t-1$, respectively; *Market Value* is the natural logarithm of the market value (in US dollars) on day $t-1$ of the government bond market portfolio. *Rating* is the rating-based credit risk; it is computed as the average score on day $t-1$ from Moody's, S&P and Fitch of the numerical sovereign ratings of the government bonds in the index. The variables *GDP, Inflation* and *Unemployment* are the GDP growth rate, the inflation rate and the unemployment rate, respectively. All regressions include weekday dummies. Year dummies are included in columns 1, 3 and 5 in the regression model; they are replaced by a year trend in columns 2, 4 and 6. We use standard errors clustered by country, which are robust to within-country serial correlation and heteroskedasticity. Standard errors are shown in parentheses beneath the regression coefficients. To improve the readability of the tables, we multiply all the coefficients and standard errors by 10,000. Obs. and R^2 denote the number of observations and the coefficient of determination, respectively. The sample period runs from 1 January 1980, to 18 September 2020. The cross-section comprises 31 countries.

***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

TABLE 8 Cold temperature shocks and sovereign bond returns.

	(1)	(2)	(3)	(4)	(5)	(6)
HDD Max	−0.020	−0.022				
	(0.016)	(0.016)				
HDD Min			−0.033***	−0.034***		
			(0.013)	(0.012)		
HDD Avg					−0.047***	−0.041***
					(0.013)	(0.014)
Convexity	−0.490***	−0.302**	−0.491***	−0.309**	−0.491*	−0.304**
	(0.163)	(0.150)	(0.163)	(0.151)	(0.163)	(0.150)
Duration	6.850**	3.470	6.840**	3.490	6.850**	3.430
	(2.780)	(2.600)	(2.780)	(2.600)	(2.780)	(2.600)
Market value	−0.042	−0.038	−0.044	−0.040	−0.042	−0.039
	(0.039)	(0.037)	(0.039)	(0.037)	(0.039)	(0.037)
GDP	0.088	0.058	0.092	0.063	0.091	0.060
	(0.104)	(0.099)	(0.105)	(0.100)	(0.105)	(0.099)
Inflation	0.486***	0.356**	0.489**	0.353***	0.488***	0.359**
	(0.093)	(0.102)	(0.093)	(0.102)	(0.093)	(0.103)
Unemployment	0.277	0.211	0.278	0.213	0.277	0.209
	(0.186)	(0.176)	(0.186)	(0.176)	(0.186)	(0.176)
Rating	0.054	0.056	0.042	0.038	0.046	0.051
	(0.300)	(0.221)	(0.300)	(0.222)	(0.301)	(0.223)
Year trend		0.134**		0.139**		0.139**
		(0.063)		(0.064)		(0.063)
Weekday dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	No	Yes	No	Yes	No
Obs.	215,461	215,461	215,461	215,461	215,461	215,461
R^2	0.003	0.001	0.003	0.001	0.003	0.001

Note: This table reports the results from fixed-effects regressions estimating the effect of temperature on sovereign bond returns. The dependent variable is country *i*'s sovereign 10-year bond return on day *t*. *HDD Max*, *HDD Min* and *HDD Avg* are the daily maximum, minimum and average heating degree days for country *i* on day *t*, respectively; they are calculated as $HDD_{i,t} = MAX\{65 - Temp_{i,t}, 0\}$. *Convexity* and *Duration* are the average adjusted convexity and duration of the bond market index on day *t*−1, respectively; *Market Value* is the natural logarithm of the market value (in US dollars) on day *t*−1 of the government bond market portfolio. *Rating* is the rating-based credit risk; it is computed as the average score on day *t*−1 from Moody's, S&P and Fitch of the numerical sovereign ratings of the government bonds in the index. The variables *GDP, Inflation* and *Unemployment* are the GDP growth rate, the inflation rate and the unemployment rate, respectively. All regressions include weekday dummies. Year dummies are included in columns 1, 3 and 5 in the regression model; they are replaced by a year trend in columns 2, 4 and 6. We use standard errors clustered by country, which are robust to within-country serial correlation and heteroskedasticity. Standard errors are shown in parentheses beneath the regression coefficients. To improve the readability of the tables, we multiply all the coefficients and standard errors by 10,000. Obs. and R^2 denote the number of observations and the coefficient of determination, respectively. The sample period runs from 1 January 1980 to 18 September 2020. The cross-section comprises 31 countries.

***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

4.5.3 | Lagged dependent variable

We continue analysing the robustness of our main results by including the lagged sovereign bond returns as an additional explanatory variable. This variation to the baseline regression model is motivated by a number of matters. These include the presence of market inefficiencies, non-synchronous trading and, more generally, unobserved or uncontrolled determinants of short-term deviations of the prices of sovereign bonds from their fundamentals that are unrelated to temperature anomalies.

The results are displayed in Table A4, in the Supporting Information Appendix. The models are estimated by means of the fixed-effects (Panel A), random-effects (Panel B) and panel-OLS (Panel C) estimation methods. For the sake of brevity, coefficient estimates for control variables are not reported. The results indicate that lagged sovereign bond return exerts a positive and significant influence on the contemporaneous sovereign bond return. Importantly, the inclusion of the lagged dependent variable does not seem to dwarf the temperature effects. For all specifications, the temperature effect is positive and generally significant. Moreover, the autoregressive effect (of the lagged dependent variable) is both positive and significant. Although we report results from the three estimation methods, the fixed and random effects estimator of a dynamic panel data (DPD) model may be biased and inconsistent (Nickell, 1981). However, in panels with a large time series dimension (T), the bias is very limited. Nickell (1981) shows that when $T \rightarrow \infty$, the asymptotic bias is given by $\underset{N\rightarrow\infty}{\text{plim}}(\hat{\rho} - \rho) \cong \frac{-(1+\rho)}{T-1}$, where ρ is the autoregressive coefficient, $\hat{\rho}$ is the least squares dummy variable (LSDV) estimator of ρ and N is the number of countries in the cross-section. The asymptotic bias tends to zero for large values of T. It is also worth noting that although alternative estimators of the DPD model yield consistent estimates, they may be less efficient than the bias-corrected LSDV estimator. For instance, Kiviet (1995) asserts that the LSDV estimator has a relatively small dispersion compared with the Anderson-Hsiao instrumental variable (IV) estimators and various generalized method of moments (GMM) estimators. Further, Bun and Carree (2005) argue that unbiased IV/GMM estimators may require additional decisions; for instance, which and how many instruments to use.

4.5.4 | Controlling for crises

The sample period spans the Global Financial Crisis and the European Debt Crisis, which could have driven sovereign bond returns. Specifically, O'Sullivan and Papavassiliou (2020) provide supporting evidence for the flight-to-liquidity phenomenon, as liquidity deteriorates during episodes of financial market stress. This phenomenon can drive sovereign credit risk, bond market volatility and returns. This highlights the need for controlling those episodes for financial market stress. Therefore, informed by O'Sullivan and Papavassiliou (2020), we construct a binary variable **gfc** (Global Financial Crisis), which takes on value one for the period from August 2007 to October 2009 (i.e., the period that spans the subprime-mortgage crisis in the United States and the Global Financial Crisis) and takes on value 0 otherwise. Similarly, we construct a binary variable **eurodebtc** (European Debt Crisis), which takes a value of 1 for the period from November 2009 to December 2012 and takes a value of 0 otherwise. Then, we estimate econometric models, in which we incorporate these two variables in lieu of the year-fixed effects or the time trend. Having accounted for the crises, the temperature effects on sovereign bond returns remain qualitatively similar. The results are documented in the Table A5, in the Supporting Information Appendix.

4.5.5 | High- and low-temperature regimes

To further explore the differential effects of the nature of asymmetries and non-linearities across high and low temperatures, we divide the dataset into the high-temperature sample and the low-temperature sample. The high-temperature sample (please see Supporting Information Appendix, Table A6, Panel A) includes bond-day observations where the temperature variable is higher or equal to the threshold, determined by the quadratic models. The low-temperature sample (Supporting Information Appendix, Table A6, Panel B) includes bond-day observations where the temperature variable is lower than the threshold, determined by the quadratic models. Panel A shows that, in the high-temperature sample, air temperature exerts a positive and significant effect on sovereign bond returns. However, in Panel B, this effect is negative and significant. This lends support to the macroeconomic paradigm.

4.5.6 | Panel vector autoregression

We have also sought to consider the presence of an endogeneity bias. Arguably, the possible reverse causality—one of the causes for an endogeneity bias—can be ruled out in this setting, as scenarios in which sovereign bond returns can drive changes in air temperature seem to be implausible. However, we recognize that an endogeneity bias can arise due to an unanticipated change in a third variable that drives both sovereign bond returns and temperature. Therefore, as an alternative identification strategy, we employ a panel vector autoregression model, in which sovereign bond returns and air temperature are regarded as the dependent variables. First, the panel Granger non-causality test between the 10-year sovereign bond return and the average temperature variable (assuming five lags) shows that at the 1% significance level, the temperature is causal to bond returns. We then simulate panel impulse-response functions. To this end, we employ the Chokesky factorization scheme to identify structural random disturbances. Underlying the Cholesky identification is the assumption that a change in air temperature can influence sovereign bond returns on the same day, whereas an unanticipated bond return cannot influence air temperature on the same day. The impulse–response function indicates that a shock to temperature (which can be thought of as including the unobserved and/or uncontrolled factors) exerts a positive and significant effect on sovereign bond returns. Due to the space constraint, the results are not reported here but are available from the authors upon request.

4.5.7 | Detrended temperature

It is worth noting that the previously scrutinized results are obtained using the *daily temperature level* (Cao & Wei, 2005a; Kamstra et al., 2003). We carry out further robustness checks, replacing the daily temperature level with *detrended* temperature series. The trend in temperature may not only be caused by the effects of global warming but also by urbanization, which leads to local warming due to the heat of buildings and reduced air circulation (Dorfleitner & Wimmer, 2010). The detrended temperature is computed by subtracting the moving average of daily temperature over the past 261 trading days (the average number of trading days in a year). Arguably, the trend, measured with the moving average, entails a slowly moving component, which can be more predictable by sovereign bond investors than fluctuations around the trend.

Consequently, the trend is less likely to drive returns on sovereign bonds. By contrast, fluctuations around the trend carry information about daily temperature, thus providing new information priced in sovereign bond markets. Hence, in Tables A7–A13, we report the results for the linear regression (Table A7, Supporting Information Appendix), the regression model that additionally features SAD (Table A8, Supporting Information Appendix), the quadratic regression (Table A9, Supporting Information Appendix), the quadratic regression with SAD (Table A10, Supporting Information Appendix), the linear regression for four different sovereign bond maturities (Table A11, Supporting Information Appendix), the fixed-effects—and panel OLS—regressions (Table A12, Supporting Information Appendix), as well as a battery of linear regressions with the lagged return as an additional explanatory variable (Table A13, Supporting Information Appendix). The results confirm our baseline findings. We find a positive and significant effect of the detrended temperature on sovereign bond returns.

5 | CONCLUSIONS

The relationship between sovereign bond returns is founded on three competing paradigms: macroeconomic, behavioral and energy demand-based. The macroeconomic paradigm implies that a positive temperature leads to a devaluation of risky variable income securities through a higher patent obsolescence rate, lower labor productivity and lower capital quality. As a result, investors liquidate their holdings of risky assets to invest in less risky or risk-free securities. This leads to a positive relationship between sovereign bond returns and temperature rises. The behavioral paradigm implies that both low and high temperatures can lead to behavioral changes in aggression and apathy. Consequently, investors' risk aversion may increase on warm days and decrease on cold ones. The energy-based view posits that both positive and negative temperature shifts lead to higher energy-related costs for firms; this is because both cold and hot temperature shocks trigger higher energy demand. Faced with increased energy costs, firms become more leveraged and—thus—more risky investment vehicles. Which of the theoretical mechanisms receive(s) support from the data?

To answer this question, an examination of four decades of daily data from 31 countries is carried out. To be specific, we test three hypotheses. First, we provide evidence of a positive and significant effect of temperature on sovereign bond returns, confirming hypothesis H1. Overall, a 10°F increase in the daily temperature raises the payoffs on sovereign bonds by a range between 0.22 and 0.85 basis points. However, the estimated quadratic relation between temperature and returns indicates that—consistently with hypothesis H2—the positive effect materializes when a certain threshold temperature level, estimated within a range between 25.38°F (−3.68°C) and 50.33°F (10.18°C), is reached. Specifically, when the daily temperature increases by 10°F above the average temperature of 58.58°F, the 10-year sovereign bond return increases by 0.535 basis points. Moreover, the test of hypothesis H3 indicates that—while hot air temperature shocks positively affect sovereign bond returns (as expected)—cold temperature shocks do not translate into an increase in sovereign bond returns. The results are robust to many considerations, survive the impact of various control variables and hold for different bond maturities and temperature measures.

First, our results support the macroeconomic paradigm, according to which climate change can dampen investment expenditure growth via at least three theoretical channels: patent obsolescence, labor productivity and capital quality channels. Within this paradigm, the results agree with the view that investors anticipate quadratic losses in both the economy and financial markets that are caused by global warming, climate change and natural disasters. Moreover, consistently with the behavioral paradigm, the temperature anomaly of Cao and Wei (2005a) implies that low (high) temperature favours high (low) stock returns. In this paper, we argue that this may be accompanied by a reverse phenomenon in the sovereign bond markets. Low temperature leads to a higher risk appetite, diverting capital flows from bonds. On the other hand, higher temperature supports safer investments—increasing bond demand. In consequence, the air temperature may be positively associated with sovereign bond returns.

Our study provides new insights into asset pricing within international government bond markets. It allows for a better understanding of the sources of return variation in sovereign bonds as well as the role of both weather and mood in this dynamic; it also sheds light on the implications of macroeconomic and energy demand-based theoretical channels. A key limitation of our research is that our empirical framework does not disentangle between behavioral and macroeconomic channels that underly the relation between temperature and sovereign bond returns. Therefore, future research—informed by general or partial equilibrium models—may seek to ascertain which channels prevail and when in this nexus between temperature and sovereign bond returns.

Admittedly, our research scrutinizes the *short-term* temperature effects on sovereign bond returns. We do not consider whether and, if so, how both government and regulatory responses to climate change are priced in international government bond markets. For instance, short-term gains can be reversed if governments decide to either fund or subsidize public investment projects that aim to mitigate or adapt to climate change. For example, Donadelli et al. (2021) find that temperature risk generates welfare costs of 93.14% of lifetime utility, which can be offset by subsidizing investment or R&D expenditure. Such subsidies can require borrowing, which gives rise to increased public debt levels; this gives rise to a higher interest rate and—thus—affects *long-run* sovereign bond returns.

In addition to the *indirect* implications for policymakers, our results also directly affect policymakers and financial regulators. Specifically, sovereign bonds are extensively used as collateral in lending transactions across countries by both financial and nonfinancial institutions (Acharya et al., 2021; Mai Nguyen & zu Knyphausen-Aufseß, 2014). If the collateral value of debt instruments increases in the short run, credit expands and access to finance improves. However, the collateral value can decrease in the long run if the government decides to embark on an expansionary fiscal policy. Thus, our research also sheds light on the trade-off between short -and long-run goals of policymakers and regulators; it also helps in underscoring the need to balance these goals optimally.

Future studies on the topics explored in this article may be extended to other asset classes. Existing evidence has demonstrated the temperature effect primarily in equities and government bonds. However, whether it exists in corporate bonds or cryptocurrencies remains an unanswered question.

ACKNOWLEDGEMENTS

We are grateful to the Guest Editors of the Special Issue "Climate risk: policy responses, financial market impacts and corporate risk-management," two anonymous reviewers, participants at the 8th Indonesian Financial Association International Conference, 11th International Conference of the Financial Engineering and Banking Society "Climate Change, Regulatory Responses and Sustainable Finance," International Webinar "Sustainable Finance and Impact Investing" and seminar participants at the Institute for Advanced Research of Shanghai University of Finance and Economics for their valuable feedback to improve our paper. We also thank Michel Haddad, Md Luftur Rahman and Daniel R. Weagley for helpful comments and suggestions. All errors are our own. Adam Zaremba acknowledges the support of the National Science Centre of Poland (grant no. 2019/33/B/HS4/01021).

ORCID

Renatas Kizys https://orcid.org/0000-0001-9104-1809
Zaghum Umar https://orcid.org/0000-0002-0425-2665
Adam Zaremba https://orcid.org/0000-0001-5879-9431

ENDNOTES

[1] See, for example, Saunders (1993), Hirshleifer and Shumway (2003), Kamstra et al. (2003), Loughran and Schultz (2004), Goetzmann and Zhu (2005), Lucey and Dowling (2005), Chang et al. (2008), Bassi et al. (2013), Goetzmann et al. (2015) and Balvers et al. (2017).

[2] Transition risk is the cost of transitioning countries to a greener economy. Physical risk refers to the physical effects of climate change, which translates into economic losses for both businesses and sovereigns. See, for example, The Financial Times article "Why Climate Change Also Matters for Government Bond Investing," https://www.ft.com/brandsuite/ftse-russell/why-climate-change-also-matters-for-government-bond-investing.html, accessed on 22 November, 2021.

[3] There is a wide consensus that bonds in general, and sovereign bonds in particular, are safer than stocks. For instance, Connolly et al. (2005), Baele et al. (2010) and Yang et al. (2009), among many others, argue that the negative correlation between stock and bond returns observed since 1997 reflect a "flight-to-safety" phenomenon, where investors switch from stocks to (safer) bonds in times of increased stock market uncertainty. Hagendorff et al. (2018) provide evidence suggesting that sovereign bonds are, on average, safer than the other assets held by their international sample of banks. It is worth noting, however, that bonds are not risk-free securities. In this vein, Longstaff et al. (2011) find that sovereign credit risk is driven by many factors including risk premiums, investment flows and country-specific fundamentals. Sène et al. (2021) and Zarmba et al. (2021b) demonstrate that the risk premiums of sovereign bonds increase in response to COVID-19.

[4] To name just a few early studies, see, for example, Wyndham (1969), Bell and Baron (1976), Moos (1975), Allen and Fischer (1978) and Cunningham (1979). For a more recent literature survey, see Pilcher et al. (2002).

[5] Please see https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily.

[6] Please see https://globalfinancialdata.com/.

[7] It is worth mentioning that we initially considered accounting for day fixed effects. However, instead we decided to control for year fixed effects. The reason is two-fold. First, conceptually, year-fixed effects are better able to integrate out long-run structural variations in the bond market profitability and climate change dynamics. Second, statistically, the time-series dimension features a daily frequency, running from January 1980 to September 2020, which comprises 10,000 + trading days. The use of day fixed effects would imply a significant degree of freedom loss, which could lead to a reduction in the estimator's efficiency.

[8] The temperature threshold for the minimum temperature variable can be calculated as $T^{*}_{i,t} = -\frac{\beta_1}{2\beta_2} = -\frac{0.066}{2 \times 0.0013} = 25.38°F$, where as for the average temperature the temperature threshold is calculated as $Temp^{*}_{i,t} = -\frac{\beta_1}{2\beta_2} = -\frac{0.151}{2 \times 0.0015} = 50.33°F$

[9] The estimates differ across the maximum, minimum and average temperature measures.

REFERENCES

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. (2017). *When should you adjust standard errors for clustering?* (No. w24003). National Bureau of Economic Research.

Acharya, V., Pierret, D., & Steffen, S. (2021). Lender of last resort, buyer of last resort, and a fear of fire sales in the sovereign bond market. *Financial Markets, Institutions & Instruments*, *30*(4), 87–112.

Allen, M. A., & Fischer, G. J. (1978). Ambient temperature effects on paired associate learning. *Ergonomics*, *21*(2), 95–101.

Andrikopoulos, A., Wang, C., & Zheng, M. (2019). Is there still a weather anomaly? An investigation of stock and foreign exchange markets. *Finance Research Letters*, *30*, 51–59.

Antweiler, W., Copeland, B. R., & Taylor, M. S. (2001). Is free trade good for the environment? *American Economic Review*, *91*(4), 877–908.

Apergis, N. (2015). Newswire messages and sovereign credit ratings: Evidence from European countries under austerity reform programmes. *International Review of Financial Analysis*, *39*, 54–62.

Baele, L., Bekaert, G., & Inghelbrecht, K. (2010). The determinants of stock and bond return comovements. *The Review of Financial Studies*, *23*(6), 2374–2428.

Bai, J., Bali, T. G., & Wen, Q. (2016). Do the distributional characteristics of corporate bonds predict their future returns? Georgetown McDonough School of Business Research Paper No. 2548562. *SSRN*. https://ssrn.com/abstract=2548562

Baltussen, G., Swinkels, L., & Van Vliet, P. (2021). Global factor premiums. *Journal of Financial Economics*, *142*(3), 1128–1154.

Balvers, R., Du, D., & Zhao, X. (2017). Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *Journal of Banking & Finance*, *77*, 18–34.

Bansal, R., & Ochoa, M. (2011). *Temperature, aggregate risk, and expected returns*(No. w17575). National Bureau of Economic Research.

Baron, R. A., & Ransberger, V. M. (1978). Ambient temperature and the occurrence of collective violence: The "long, hot summer" revisited. *Journal of Personality and Social Psychology*, *36*(4), 351–360.

Bassi, A., Colacito, R., & Fulghieri, P. (2013). 'O sole mio: An experimental analysis of weather and risk attitudes in financial decisions. *Review of Financial Studies*, *26*(7), 1824–1852.

Beirne, J., & Fratzscher, M. (2013). The pricing of sovereign risk and contagion during the European sovereign debt crisis. *Journal of International Money and Finance*, *34*, 60–82.

Bell, P. A. (1981). Physiological, comfort, performance, and social effects of heat stress. *Journal of Social Issues*, *37*(1), 71–94.

Bell, P. A., & Baron, R. A. (1976). Aggression and heat: The mediating role of negative affect. *Journal of Applied Social Psychology*, *6*(1), 18–30.

Boudoukh, J., Brooks, J., Richardson, M., & Xu, Z. (2021). Sovereign credit quality and violations of the law of one price. *Review of Finance*, *25*(5), 1581–1607.

Boyd, J. H., Hu, J., & Jagannathan, R. (2005). The stock market's reaction to unemployment news: Why bad news is usually good for stocks. *The Journal of Finance*, *60*(2), 649–672.

Bun, M. J. G., & Carree, M. A. (2005). Bias-corrected estimation in dynamic panel data models. *Journal of Business & Economic Statistics*, *23*(2), 200–210.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global nonlinear effect of temperature on economic production. *Nature*, *527*(7577), 235–239.

Cantor, R., & Packer, F. (1996). Determinants and impact of sovereign credit ratings. *FRBNY Economic Policy Review*, *2*(2), 37–54.

Cao, M., & Wei, J. (2005a). Stock market returns: A note on temperature anomaly. *Journal of Banking & Finance*, *29*(6), 1559–1573.

Cao, M., & Wei, J. (2005b). An expanded study on the stock market temperature anomaly. In A. H. Chen (Ed.), *Research in Finance* (Vol. 22, pp. 73–112). Emerald Group Publishing Limited.

Chang, S. C., Chen, S. S., Chou, R. K., & Lin, Y. H. (2008). Weather and intraday patterns in stock returns and trading activity. *Journal of Banking & Finance*, *32*(9), 1754–1766.

Chang, T., Nieh, C. C., Yang, M. J., & Yang, T. Y. (2006). Are stock market returns related to the weather effects? Empirical evidence from Taiwan. *Physica A: Statistical Mechanics and its Applications*, *364*, 343–354.

Chen, X., & Yang, L. (2019). Temperature and industrial output: Firm-level evidence from China. *Journal of Environmental Economics and Management*, *95*, 257–274.

Chiah, M., & Zhong, A. (2019). Day-of-the-week effect in anomaly returns: International evidence. *Economics Letters*, *182*, 90–92.

Colacito, R., Hoffmann, B., & Phan, T. (2019). Temperature and growth: A panel analysis of the United States. *Journal of Money, Credit and Banking*, *51*(2–3), 313–368.

Connolly, R., Stivers, C., & Sun, L. (2005). Stock market uncertainty and the stock–bond return relation. *Journal of Financial and Quantitative Analysis*, *40*(1), 161–194.

Cunningham, M. R. (1979). Weather, mood and helping behavior: Quasi-experiment with the sunshine samaritan. *Journal of Personality and Social Psychology*, *37*, 1947–1956.

Dell, M., Jones, B. F., & Olken, B. A. (2009). Temperature and income: Reconciling new cross-sectional and panel estimates. *American Economic Review*, *99*(2), 198–204.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95.

Deryugina, T., & Hsiang, S. M. (2014). *Does the environment still matter? Daily temperature and income in the United States* (No. w20750). National Bureau of Economic Research.

Donadelli, M., Grüning, P., Jüppner, M., & Kizys, R. (2021). Global temperature, R&D expenditure, and growth. *Energy Economics*, *104*, 105608.

Dorfleitner, G., & Wimmer, M. (2010). The pricing of temperature futures at the Chicago Mercantile Exchange. *Journal of Banking & Finance*, *34*(6), 1360–1370.

Du, D., Zhao, X., & Huang, R. (2017). The impact of climate change on developed economies. *Economics Letters*, *153*, 43–46.

Dufrénot, G., Gente, K., & Monsia, F. (2016). Macroeconomic imbalances, financial stress and fiscal vulnerability in the euro area before the debt crises: A market view. *Journal of International Money and Finance*, *67*, 123–146.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, *105*(3), 457–472.

Fama, E. F., & French, K. R. (2017). International tests of a five-factor asset pricing model. *Journal of Financial Economics*, *123*(3), 441–463.

Fisher, A. C., Hanemann, W. M., Roberts, M. J., & Schlenker, W. (2012). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: Comment. *American Economic Review*, *102*(7), 3749–3760.

Floros, C. (2011). On the relationship between weather and stock market returns. *Studies in Economics and Finance*, *28*(1), 5–13.

Geczy, C., & Samonov, M. (2017). Two centuries of multi-asset momentum (equities, bonds, currencies, commodities, sectors and stocks). SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2607730

Gelman, A. (2005). Analysis of variance—Why it is more important than ever. *The Annals of Statistics*, *33*(1), 1–53.

Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate finance. *Annual Review of Financial Economics*, *13*, 15–36.

Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2015). Weather-induced mood, institutional investors, and stock returns. *Review of Financial Studies*, *28*(1), 73–111.

Goetzmann, W. N., & Zhu, N. (2005). Rain or shine: Where is the weather effect? *European Financial Management*, *11*(5), 559–578.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, *32*(1), 1–26.

Green, B. F., & Tukey, J. W. (1960). Complex analyses of variance: General problems. *Psychometrika*, *25*(2), 127–152.

Hagendorff, J., Keasey, K., & Vallascas, F. (2018). When banks grow too big for their national economies: Tail risks, risk channels, and government guarantees. *Journal of Financial and Quantitative Analysis*, *53*(5), 2041–2066.

He, J., & Ma, X. (2021). Extreme temperatures and firm-level stock returns. *International Journal of Environmental Research and Public Health*, *18*(4), 2004.

Heyes, A., & Saberian, S. (2019). Temperature and decisions: Evidence from 207,000 court cases. *American Economic Journal: Applied Economics*, *11*(2), 238–265.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance*, *58*(3), 1009–1032.

Horowitz, J. K. (2009). The income-temperature relationship in a cross-section of countries and its implications for predicting the effects of global warming. *Environmental and Resource Economics*, *44*, 475–493.

Hou, J., Shi, W., & Sun, J. (2019). Stock returns, weather, and air conditioning. *PLoS One*, *14*(7), e0219439.

Howarth, E., & Hoffman, M. S. (1984). A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology*, *75*(1), 15–23.

Hu, H., Wei, W., & Chang, C. P. (2022). Examining the impact of extreme temperature on green innovation in China: Evidence from city-level data. *Energy Economics*, *114*, 106326.

Huang, T., Wu, F., Yu, J., & Zhang, B. (2015). International political risk and government bond pricing. *Journal of Banking & Finance*, *55*, 393–405.

Hübler, M., Klepper, G., & Peterson, S. (2008). Costs of climate change: The effects of rising temperatures on health and productivity in Germany. *Ecological Economics*, *68*(1–2), 381–393.

ICMA (2020) Bond Market Size. Available at: https://www.icmagroup.org/market-practice-and-regulatory-policy/secondary-markets/bond-market-size/ (Accessed: December 21st, 2023)

Ilmanen, A., Israel, R., Moskowitz, T. J., Thapar, A. K., & Lee, R. (2021). How do factor premia vary over time? A century of evidence. *Journal of Investment Management*, *19*(4), 15–57.

Imbens, G. W., & Kolesár, M. (2016). Robust standard errors in small samples: Some practical advice. *Review of Economics and Statistics*, *98*(4), 701–712.

Jacobsen, B., & Marquering, W. (2008). Is it the weather? *Journal of Banking & Finance*, *32*(4), 526–540.

Jacobsen, B., & Marquering, W. (2009). Is it the weather? Response. *Journal of Banking & Finance*, *33*(3), 583–587.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: A SAD stock market cycle. *American Economic Review*, *93*(1), 324–343.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2009). Is it the weather? Comment. *Journal of Banking & Finance*, *33*(3), 578–582.

Katz, R. W. (2010). Statistics of extremes in climate change. *Climatic Change*, *100*(1), 71–76.

Kaustia, M., & Rantapuska, E. (2016). Does mood affect trading behavior? *Journal of Financial Markets*, *29*, 1–26.

Keef, S. P., & Roush, M. L. (2002). The weather and stock returns in New Zealand. *Quarterly Journal of Business and Economics*, *41*(1/2), 61–79.

Keef, S. P., & Roush, M. L. (2007). Daily weather effects on the returns of Australian stock indices. *Applied Financial Economics*, *17*(3), 173–184.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), 1053–1069.

Kilian, L., & Park, C. (2009). The impact of oil price shocks on the U.S. stock market. *International Economic Review*, *50*, 1267–1287.

Kinateder, H., & Papavassiliou, V. G. (2019). Sovereign bond return prediction with realized higher moments. *Journal of International Financial Markets, Institutions and Money*, *62*, 53–73.

Kiviet, J. F. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. *Journal of Econometrics*, *68*(1), 53–78.

Kumar, M. M. S., & Baldacci, M. E. (2010). *Fiscal deficits, public debt, and sovereign bond yields (No. 2010/184)*. International Monetary Fund.

Lau, N. C., & Nath, M. J. (2012). A model study of heat waves over North America: Meteorological aspects and projections for the twenty-first century. *Journal of Climate*, *25*(14), 4761–4784.

Li, Y. (2021). Investor sentiment and sovereign bonds. *Journal of International Money and Finance*, *115*, 102388.

Longstaff, F. A., Pan, J., Pedersen, L. H., & Singleton, K. J. (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics*, *3*(2), 75–103.

Loughran, T., & Schultz, P. (2004). Weather, stock returns, and the impact of localized trading behavior. *Journal of Financial and Quantitative Analysis*, *39*(2), 343–364.

Lucey, B. M., & Dowling, M. (2005). The role of feelings in investor decision making. *Journal of Economic Surveys*, *19*(2), 211–237.

Mai Nguyen, J., & zu Knyphausen-Aufseß, D. (2014). The impact of sovereign credit ratings on corporations: A literature review and research recommendations. *Financial Markets, Institutions & Instruments*, *23*(3), 125–178.

Makkonen, A., Vallström, D., Uddin, G. S., Rahman, M. L., & Haddad, M. F. C. (2021). The effect of temperature anomaly and macroeconomic fundamentals on agricultural commodity futures returns. *Energy Economics*, *100*, 105377.

Moos, R. H. (1975). *The human context: Environmental determinants of behavior*. Wiley.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*(6), 1417–1426.

Oliveira, L., Curto, J. D., & Nunes, J. P. (2012). The determinants of sovereign credit spread changes in the Euro-zone. *Journal of International Financial Markets, Institutions and Money*, *22*(2), 278–304.

O'Sullivan, C., & Papavassiliou, V. G. (2020). On the term structure of liquidity in the European sovereign bond market. *Journal of Banking & Finance*, *114*, 105777.

Palamarek, D. L., & Rule, B. G. (1979). The effects of ambient temperature and insult on the motivation to retaliate or escape. *Motivation and Emotion*, *3*(1), 83–92.

Peillex, J., El Ouadghiri, I., Gomes, M., & Jaballah, J. (2021). Extreme heat and stock market activity. *Ecological Economics*, *179*, 106810.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, *22*(1), 435–480.

Pilcher, J. J., Nadler, E., & Busch, C. (2002). Effects of hot and cold temperature exposure on performance: A meta-analytic review. *Ergonomics*, *45*(10), 682–698.

Sariannidis, N., Giannarakis, G., & Partalidou, X. (2016). The effect of weather on the European stock market: The case of Dow Jones Sustainability Europe Index. *International Journal of Social Economics*, *43*(9), 943–958.

Saunders, E. M. (1993). Stock prices and wall street weather. *American Economic Review*, *83*(5), 1337–1345.

Searle, S. R., Casella, G., & McCulloch, C. E. (2009). *Variance components* (Vol. 391). John Wiley & Sons.

Sène, B., Mbengue, M. L., & Allaya, M. M. (2021). Overshooting of sovereign emerging eurobond yields in the context of COVID-19. *Finance Research Letters*, *38*, 101746.

Sheikh, M. F., Shah, S. Z. A., & Mahmood, S. (2017). Weather effects on stock returns and volatility in South Asian markets. *Asia-Pacific Financial Markets*, *24*(2), 75–107.

Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics*, *142*(2), 487–498.

Tzouvanas, P., Kizys, R., Chatziantoniou, I., & Sagitova, R. (2019). Can variations in temperature explain the systemic risk of European firms? *Environmental and Resource Economics*, *74*(4), 1723–1759.

Vose, R. S., Applequist, S., Bourassa, M. A., Pryor, S. C., Barthelmie, R. J., Blanton, B., Bromirski, P. D., Brooks, H. E., Degaetano, A. T., Dole, R. M., Easterling, D. R., Jensen, R. E., Karl, T. R., Katz, R. W., Klink, K., Kruk, M. C., Kunkel, K. E., MacCracken, M. C., Peterson, T. C., … Young, R. S. (2014). Monitoring and understanding changes in extremes: Extratropical storms, winds, and waves. *Bulletin of the American Meteorological Society*, *95*(3), 377–386.

Weagley, D. (2019). Financial sector stress and risk sharing: Evidence from the weather derivatives market. *The Review of Financial Studies*, *32*(6), 2456–2497.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. MIT Press.

Wyndham, C. H. (1969). Adaptation to heat and cold. *Environmental Research*, *2*, 442–469.

Yan, Y., Xiong, X., Li, S., & Lu, L. (2022). Will temperature change reduce stock returns? Evidence from China. *International Review of Financial Analysis*, *81*, 102112.

Yang, J., Zhou, Y., & Wang, Z. (2009). The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence. *Journal of Banking & Finance*, *33*(4), 670–680.

Yoon, S. M., & Kang, S. H. (2009). Weather effects on returns: Evidence from the Korean stock market. *Physica A: Statistical Mechanics and its Applications*, *388*(5), 682–690.

Zaremba, A., Kizys, R., & Aharon, D. Y. (2021a). Volatility in international sovereign bond markets: The role of government policy responses to the COVID-19 pandemic. *Finance Research Letters*, *43*, 102011.

Zaremba, A., Kizys, R., Aharon, D. Y., & Umar, Z. (2021b). Term spreads and the COVID-19 pandemic: Evidence from international sovereign bond markets. *Finance Research Letters*, *44*, 102042.

Zinman, J., & Zitzewitz, E. (2016). Wintertime for deceptive advertising? *American Economic Journal: Applied Economics*, *8*(1), 177–192.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Kizys, R., Rouatbi, W., Umar, Z., & Zaremba, A. (2024). Air temperature and sovereign bond returns. *Financial Markets, Institutions & Instruments*, *33*, 179–209. https://doi.org/10.1111/fmii.12192

AUTHOR BIOGRAPHIES

Renatas Kizys is an Associate Professor in Finance within Southampton Business School at the University of Southampton. He is also Deputy Head (Research) of Department of Banking and Finance.Renatas received BA and MA degrees in Economics from the University of Vilnius, Lithuania, and MSc and PhD in Economics from the University of Alicante, Spain. Renatas further honed his expertise through the Advanced Studies Program in International Economic Policy Research at the Kiel Institute for the World Economy in Germany. His academic journey has taken him across the globe. Prior to joining the University of Southampton, Renatas dedicated eight years to the University of Portsmouth, where he held multiple key positions. This included serving as a Reader in Finance, fulfilling the role of Interim Head of the Economics and Finance Subject Group, and overseeing research degree coordination in the Faculty of Business and Law. Renatas boasts a rich international experience, with more than three years as an Assistant Professor at the Technological Institute of Monterrey in Mexico, and a distinguished P.K. Woolley Research Fellowship at the University of York, UK. He has also held Visiting Academic positions in China, Germany, Indonesia, Italy Lithuania, and Spain.

His research portfolio spans a wide array of areas, encompassing asset pricing, cryptocurrencies, energy economics and finance, environmental economics and finance, financial risk, investor sentiment, financial asset valuation, macroeconomy and financial markets, and portfolio optimisation. He has a strong publication record in renown academic journals (e.g., British Accounting Review, Energy Economics, Energy Journal, Journal of Banking and Finance, Journal of Empirical Finance, Journal of Financial Markets, etc.).

Wael Rouatbi is an Associate Professor of Finance at Montpellier Business School. He teaches Corporate Finance, Strategic Finance, Power Platform and Financial Modelling. He obtained his PhD in Management Sciences from University of Paris–Est in 2016. Wael Rouatbi's research interests are international, covering corporate finance,corporate governance, and going private transactions. He has published several academic papers in international refereed journals including *Journal of Banking & Finance*, *Journal of Corporate Finance*, *Financial Management*, *Annals of Operations Research*, *European Financial Management*, *International Review of Financial Analysis and Global Finance Journal*. He received the 2017 Emerald/EFMD outstanding doctoral research award in the Finance category.

Dr. Zaghum Umar is working as an Associate Professor at Zayed University, Abu Dhabi, UAE. Zaghum has broad research interests in Financial Modeling, Empirical Finance, Corporate Finance, Risk Management, Emerging markets, Alternative asset classes and Strategic Asset Allocation. He has several publications in top ranked finance journals such as Journal of International Money and Finance, International Journal of financial Analysis, European Journal of Finance, Energy Economics, Economic Letters, Resources Policy, Economic Modelling, Pacific-Basin Finance, Applied Economics.

Adam Zaremba is Associate Professor of Finance at Montpellier Business School (France) and Poznan University of Economics and Business (Poland). Previously, he was an Associate Professor of Finance at the University of Dubai (UAE). His research interests include asset pricing, investment and financial markets. A graduate of the Poznan University of Economics and Business, he has studied, lectured and taught at various institutions around the world. He has worked as an economist, consultant and portfolio manager for investment management companies. Adam's work has been published in journals such as the Journal of Financial Economics, Review of Finance, Journal of Banking and Finance, and Journal of Financial Stability. He is also the author of several books on financial markets.