# Inattention to the Coming Storm? Rising Seas and Sovereign Credit Risk

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**Abstract**

This study examines whether the sovereign credit market integrates information on coastal flooding and sea level rise (SLR) hazards. Using credit default swap spreads as measures of credit quality, I find that medium- to long-term risk for sovereigns with a significant portion of their population vulnerable to ex-ante coastal flooding increases in response to climate summit news. Additionally, I document that the market asynchronously incorporates changing vulnerabilities of regions into its risk assessment with such news. In- and out-of-sample predictability tests suggest that the market lags in integrating adverse trends in exposure under projections of SLR and population growth, indicating a lack of attention to complex climate information. Finally, I demonstrate that these projections have historically been inaccurate, leading to mispricing.

**Keywords:** Climate change, sovereign risk, investor inattention, flood risk, sea level rise.

**JEL classification codes:** Q54; G12; G15; D83.

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Approximately 230 million people currently live one meter above high tide, making them vulnerable to storm surges and tidal disasters (Kulp and Strauss, 2019). As seas rise and coastal populations expand, the risk of large-scale flooding intensifies for affected nations. Financial institutions have recognized the potential national economic impact of these hazards (FSB, 2020), prompting the question addressed in this paper—are risks stemming from coastal flooding and sea level rise (SLR) incorporated into the sovereign credit market? Understanding vulnerability is crucial as credit-impaired countries may face limited debt issuance capability to address the effects of climate change, and unaccounted factors can lead to financial instability for market participants when climate risk materializes (Carney, 2015).

Studying market responses to these phenomena is challenging due to the limited time series variation of coastal surges and the slow-moving nature of SLR vulnerability. Therefore, I isolate an information channel, showing that the credit risk of countries exposed to ex-ante coastal flooding hazards increases with news regarding international climate summits.[1] This novel finding reveals that the market integrates publicly available information regarding flooding vulnerability, correctly differentiating between regions that are susceptible. Confirming the role of attention in embedding climate risks into spreads is a prerequisite to evaluating whether the market considers more complex information sets, such as long-term exposure trends influenced by SLR and demographic changes. I find that investors are slow to integrate climate and demographic projections—which have proven unreliable compared to observed data—resulting in a mispricing of risks.

Sovereign risk is assessed using credit default swap (CDS) spreads, which offer several advantages over bonds: (i) CDS instruments serve as insurance contracts that hedge against default risk, (ii) they have standardized contracts over multiple time horizons, facilitating easy comparison across countries (Augustin et al., 2020), (iii) they more rapidly reflect new credit information (Gyntelberg et al., 2018), and (iv) they tend to be more liquid than the underlying bond (Mullin and Bruno, 2020). For the empirical analyses, I use one-month changes in 1-, 5-, and 10-year spreads for 59 sovereigns from January 2010 to November 2019 to derive credit protection returns, similar to Hilscher et al. (2015).[2] This approach enables me to test whether risks are integrated with attention and to identify the relevance of the hazard across the term structure.

I begin by presenting evidence that the marginal effect of a one-standard deviation increase in global attention is related to a 69 and 80 basis point increase in the 5- and 10-year CDS returns of sovereigns exposed to coastal flooding hazard. In contrast, there is no

[1] I follow others, e.g., Engle et al. (2020), assuming that news articles offer information on climate change and increase the saliency of potential risks.

[2] This period is selected post the CDS Big Bang and the Global Financial Crisis, as there is evidence of sea level rise (SLR) pricing in other markets (Goldsmith-Pinkham et al., 2023).

significant relationship between the less exposed sovereigns and credit risk across the term structure of spreads. To put this into perspective, I compare the economic magnitude to the results from the no-arbitrage model of Doshi et al. (2017). There, a one-standard-deviation increase in the unemployment rate of their sample of countries has a comparable rise of 1.77% in spreads. In aggregate, the results illustrate that the market is pricing coastal flooding hazard contemporaneously with greater attention, particularly for longer-term spreads.

To obtain these estimates, I measure the percentage of country populations living in the 1-in-100 year floodplain, as the approach has been used in the economics and scientific literature (see Hallegatte et al. (2013); Dell et al. (2012)), is available historically, and is forecasted under different climate scenarios.[3] I acquire data from Vafeidis et al. (2011), a paper which produced the most accurate information of flooding vulnerability that the credit market would have access to at the time.[4] I define this measure as sovereign susceptibility to extreme sea level (*ESL*) hazard—a term commonly used in contemporary science (Gregory et al., 2019). Using this metric to sort the sample of sovereigns into exposure quartiles, I select the top quartile—fourteen sovereigns—as the group "more exposed" to the hazard and compare it to the bottom two quartiles, the "less exposed" group. Then, I conduct panel regressions in which I project CDS returns on a set of control variables, while also including an interaction term between an attention index of interest and the exposure indicator.

I use the international summits news index developed by Faccini et al. (2023) as a proxy for information on coastal flooding and SLR becoming more salient and subsequently influencing the credit market. I argue that the index represents "bad news" about the economy related to climate change (Engle et al., 2020)—this is because news emanating from these meetings, such as commitments and goal-setting, lack accountability and therefore also credence among investors (Hsu et al., 2015). Scientific reports detailing the extent of coastal flooding and SLR are also frequently discussed, such as Allison et al. (2011), which was written before COP15. Considering these factors, I assume that the rise in media attention surrounding international summits promulgates these hazards to the broader market.

I further confirm the relationship with six auxiliary tests. First, using an event study, I determine that sovereigns more vulnerable to *ESL* hazard increased their long-term credit risk during the lead-up to the Paris Agreement, in comparison with less-exposed counterparts. Second, I obtain data on CDS notional values from the Depository Trust and Clearing Corporation, similar to Oehmke and Zawadowski (2017), and find that weekly net notional amounts of sovereign CDS contracts are positively associated with attention to climate sum-

[3] A "1-in-100 year" flooding event has a 1% chance of occurring in any given year.

[4] 100-year floods are a commonly used hazard threshold in economics and climate literature (see Gibson and Mullins (2020) and Hallegatte et al. (2013)). I also crosscheck flood protection standards from Lincke and Hinkel (2018) and set exposure to zero if a country is protected from a 1-in-100-year flooding event.

mits. Third, I use the reduced-form sovereign credit model developed by Pan and Singleton (2008) to estimate the risk premium from the term structure of spreads. The fundamental idea is that the increase in attention is associated with an unexpected rise in the probability that a sovereign suffers a negative credit event—in this case, a devastating coastal flood causing a missed interest payment or a debt restructuring. After the decomposition, I conduct regressions to confirm that risk premiums follow a similar pattern to the main results. Fourth, I use country-level Google search volumes related to United Nations Climate Change conferences as an alternative measure of attention. Fifth, I show that the results are unchanged after controlling for liquidity. Finally, including other climate risk factors does not alter the findings. This set of results is crucial as it affirms the face validity of measuring vulnerability with population exposure as well as the synchronous mechanism between attention and risk pricing in the CDS returns.

Next, I investigate if the market considers a more complex information set, the changes in coastal flooding exposure—$\Delta ESL$ hazard. The risk is material as the long-run compounding effects of coastal population growth and SLR exponentially increase the severity and likelihood of damaging floods (Taherkhani et al., 2020). This is measured in two ways: (i) by evaluating observed population growth trends, and (ii) by using forecasts of SLR and population growth developed in Vafeidis et al. (2011). To assess changes in vulnerability, I estimate each sovereign's annual rate of change in susceptibility by regressing its population vulnerable to 1-in-100-year floods on a linear time trend. These coefficients reveal considerable cross-sectional variation, with some countries showing reduced risk due to inland population shifts. Furthermore, observed and projected data yield markedly different values.[5] To denote exposure, I select countries vulnerable to $ESL$ hazard and further split them into groups according to the sign and magnitude of estimate rates obtained from either using observed or projected climate and population data. Once again, the exposure indicator is interacted with an index to understand the relationship between CDS returns and global attention to climate change and international summits.

The empirical results indicate no statistically significant difference in 5- or 10-year CDS returns between more vulnerable and less vulnerable sovereigns, whether using observed or projected data. What market frictions might be preventing differentiation between countries with adverse or more favorable SLR exposure trends? A behavioral channel, as developed in Hirshleifer (2001), would suggest that investors and markets can be inattentive to signals and make systematic errors, particularly when information is sparse. In this setting, coastal surges

[5]The reason for the disparity lies in the assumptions held by demographers and climate scientists, as the widely accepted scientific consensus used to be that populations would grow considerably faster in coastal regions than in the interior, which has not materialized. Observed trends, rather, reveal that many regions developed faster inland than on coasts.

pose a long-term threat to vulnerable sovereigns, and during periods of elevated attention, investors underreact because of the burden involved in processing information such as publicly available demographic trends or forecasts (DellaVigna and Pollet, 2007). Behavioral theories, however, require that investors are inattentive enough that return predictability is substantial when compared to rational models (Van Nieuwerburgh and Veldkamp, 2010).

To test whether the market is inattentive, I perform both in- and out-of-sample (OOS) predictability regressions. I find that the monthly OOS mean squared forecast error of a 54-month rolling window estimation, calculated in comparison to the rolling mean (Campbell and Thompson, 2008), produces an R-squared of 3.22% for more vulnerable sovereigns when using climate projections. Here, the positive and large OOS R-squared values indicate that market participants are sluggish in incorporating $\Delta ESL$ hazard, confirming a theory of underreaction. In contrast, for the sample of sovereigns suffering from greater $\Delta ESL$ hazard based on observed trends, the out-of-sample R-squared is -0.18%. Taken together with the results of the panel regressions, the overarching findings substantiate three conclusions about the sovereign credit market: (i) a premium is ascribed to coastal flooding exposure, (ii) $\Delta ESL$ vulnerability is slow to be incorporated, and (iii) risks are mispriced as the market favors historically erroneous climate model projections over realized trends.

This study contributes to the active body of research documenting the relationship between climate change and sovereign risk. To the best of my knowledge, no previous studies have investigated whether sovereign credit markets incorporate ex-ante coastal flooding and SLR hazards. In this paper, I uncover a novel exposure metric that measures the exposure of sovereigns to coastal flooding and SLR, which credit markets appear to strongly respond to during periods of attention. Others, such as Klusak et al. (2023), provide assessments of how sovereign ratings may decrease under various climate scenarios based on GDP loss. Mallucci (2022), Boehm (2022), and Beirne et al. (2021) use ex-post disasters such as temperature shocks to reveal reductions in sovereign bond yields.

Recent scholarship that studies the nexus of SLR and risk has almost exclusively focused on either the municipal bond or property markets. I add to this literature by documenting that the risks are incorporated heterogeneously across a global financial instrument with robust external validity. Painter (2020) and Goldsmith-Pinkham et al. (2023) both show an association between flood hazard and municipal bond credit risk, although with more muted effects in comparison to the premium found in this paper. In the property market, some (Murfin and Spiegel, 2020) fail to detect any relationship between property prices and vulnerability while others (Baldauf et al. (2020); Bakkensen and Barrage (2022); Ilhan (2020); Nguyen et al. (2022)) show how heterogeneous beliefs and attention can impact prices. This study is nuanced in that it finds evidence to support both streams of the debate, documenting how market frictions lead to an underreaction to publicly available information.

A concomitant contribution is that attention, rather than climate shocks, can serve as a mechanism for the credit market to price climate risk, echoing findings by Choi et al. (2020), Engle et al. (2020), and Ardia et al. (2020). These articles, however, typically brush aside the fact that investors can underreact to news about climate change—a key outcome of this investigation.[6] This evidence suggests that the market distinguishes between relevant pieces of climate information, albeit slowly. Hong et al. (2019) present evidence of investor underreaction to country-level trends in droughts. Conversely, Schlenker and Taylor (2021) demonstrate that financial markets integrate temperature projections.

The remainder of the paper proceeds as follows. Section 1 presents a systematic development of the hypotheses. Data collection, sample creation methods, and exposure vulnerability are described in Section 2. I then present the empirical results relating attention to sovereign CDS return in Section 3.1 and discuss market efficiency in Section 3.2. I conduct robustness checks in Section 4 and conclude in Section 5.

# 1 Hypothesis Development

I outline a basic asset pricing framework to organize hypotheses that guide the empirical analyses aimed at understanding the relationship between sovereign credit risk, coastal flooding, and SLR. Sovereign CDS spreads are useful for studying climate phenomena as they measure a sovereign's aggregate financial health and credit default risk. The instrument allows a protection buyer to purchase insurance against a contingent credit event on an underlying reference entity by paying an annuity premium (spread) to the protection seller. Sovereign CDS are also useful for investigating whether the market considers $ESL$ and $\Delta ESL$ hazards as related to short, medium, or long term risks because contracts are standardized across the term structure of spreads.

Consider a simplified reduced-form pricing of credit risk where the likelihood of default is governed by a default-intensity process $\lambda$. Assuming that there has been no earlier default, the probability of default within $[t, t+dt)$ for sovereign $i$ can be defined as:

$$P[\tau_i < t + dt \mid \tau_i \geq t, \mathcal{F}_t] = \lambda_i(t)dt \tag{1}$$

where $\tau_i$ denotes the default time and $\lambda_i(t)$ depends on all publicly available information to investors at time $t$ ($t = 1, \ldots, T$) represented by the filtration process $\mathcal{F}_t$ (Duffie and

[6]Exceptions include Gande and Parsley (2005), Kim et al. (2015), and Cathcart et al. (2020) who have investigated the impact of news in sovereign credit markets. Cathcart et al. (2020), for example, finds that sovereign credit spreads underreact to general media sentiment.

Singleton, 1999). Intuitively, the intensity provides a "local" default rate which can be used to price sovereign CDS contracts. Using the definition of default intensity, the valuation for newly written sovereign CDS insurance contract for maturity $m$, can be approximated as the risk-neutral, $\mathbb{Q}$, expectation of its discounted payoff:

$$SCDS_i(m,t) = L^{\mathbb{Q}} E\left[\lambda_i(t)^{\mathbb{Q}} \mid \mathcal{F}(t)\right] \tag{2}$$

where $L^{\mathbb{Q}}$ is the fractional recovery of the face value of the contract.

I assume that the default intensity is dependent on an observable set of relevant covariates that are either sovereign specific or global. In this setting, the likelihood of default for a sovereign grows with the proportion of its population that is vulnerable to coastal flooding and SLR hazard.[7] The risk-neutral default intensity can then be stated in the affine form:

$$\lambda_i(t)^{\mathbb{Q}} = e^{(\alpha+\beta\cdot U_{i,t}+\theta\cdot V_t+\phi\cdot C_{t-h})}, \tag{3}$$

where $U_{i,t}$ is a vector containing sovereign specific covariates and $V_t$ are those that are common. $C_{t-h}$ is a vector of covariates proxying news regarding climate, coastal flooding, and SLR related topics. Here, $h$ ($h = 0, \ldots, H$) is a lag factor for how quickly this information is incorporated into CDS spreads and is critical for the developing the hypotheses. $\alpha$, $\beta$, $\theta$, and $\phi$ are functions of the information included in the contemporaneous and lagged state variables.

The base hypothesis is motivated by previous work on the time-series variation of climate news and the pricing of assets vulnerable to slow-moving hazards (Giglio et al., 2021). In this case, information regarding coastal flooding hazard becomes more salient with news media surrounding climate summits. The assumption, similar to others (Kölbel et al. (2024); Ilhan et al. (2021)), is that summits increase the perception and saliency of climate risks, which in turn increase the cost of protection for those sovereigns that have a greater proportion of their population vulnerable to coastal flooding. Information on the exposure of sovereigns to coastal flooding (i.e., *ESL* exposure) is prevalent, publicly available, and does not require specialized knowledge of climate forecasts or trends. Since the information is relatively straightforward to process for investors, this suggests that $h$ will be close to zero and that $C$ will be integrated into prices contemporaneously with news. Furthermore, considering that the probability of a flooding event is unlikely in any given year but compounds over time, *ESL* hazard can be deemed as a medium- to long-term hazard. Following this thread, I propose the following prediction:

[7] As stated earlier, Painter (2020) and Goldsmith-Pinkham et al. (2023) show how SLR can impact regional economies. Klusak et al. (2023) considers how sovereign ratings may decrease under forecasts of climate physical risk adjusted GDP which includes SLR and coastal flooding risks.

**Hypothesis $\mathbf{H_1}$:** *Greater news attention to climate summits is contemporaneously related to higher CDS spreads for sovereigns exposed to coastal flooding.*

Next, I outline how the market may consider incorporating longer-term risks, i.e., the changes in *ESL* hazard. This risk is largely dominated by demographic and SLR trends as they will act to *exponentially* increase the odds and severity of coastal flooding disasters disaster (Taherkhani et al., 2020). The information, however, is difficult to process as it requires specialized knowledge of climate and demographic projections. DellaVigna and Pollet (2007), for example, find that investors are short-sighted and neglect information on long-term demographic changes. This processing inefficiency implies that $h$ is greater than zero, dampening the signal. The information is only fully integrated in the following periods conditional on default not occurring. This observation leads to the second prediction:

**Hypothesis $\mathbf{H_2}$:** *During periods of elevated news, the sovereign credit market is slow to price long-term demographic and climate hazards, especially when information is complex.*

This prediction implies that CDS spreads are predictable when new climate information is particularly complex and difficult to process, i.e., when $h > 0$. This suggests that lagged values of news proxies should positively predict CDS spreads. Empirical evidence from Chang et al. (2022) and Wang et al. (2021) point to a systematic underreaction in spreads when there is a change to the total mix of information, supporting this conjecture.

# 2 Data and Hazard Construction

In Section 2.1, I discuss the financial data used in the empirical exercises. In Section 2.2, I explain the attention index used for the analyses. I describe in detail the methodology for calculating $ESL$ and $\Delta ESL$ hazard in sections 2.3 and 2.4.

## 2.1 Financial Data

The sovereign CDS market is a practical setting for investigating the research question because the spread responds rapidly to changes in credit events (Longstaff et al., 2011). I acquire monthly sovereign CDS spread data from Datastream for 81 distinct sovereigns. The spread data covers the 1-, 5-, and 10-year tenors, denominated in USD, with the underlying as senior unsecured debt. The CDS spread levels are used to create monthly percent changes for each country to obtain sovereign CDS returns. I restrict the sample to the time period of January 2010 through November 2019 for three reasons: (i) previous research by Goldsmith-Pinkham et al. (2023) has shown limited evidence of climate hazard being priced before 2010, (ii) to mitigate the impact of the global financial crisis, and (iii) to account for the post-CDS "big bang" era that standardized coupon and default-contingent payments. I limit the sample of sovereign CDS returns to only include sovereigns with non-missing values and those that contain more than 90% of observations as non-zero.[8] These constraints reduce the sample size to 59 sovereigns. The remaining regions used in this study are presented in Table 2. The sample consists of sovereigns from Europe, Latin America, Asia, and Africa.

Prior literature by Augustin (2018) and Dieckmann and Plank (2012) find that both country and global factors are drivers of changes in sovereign CDS spreads. I use their work as the basis for the economic and financial variables I gather at the monthly frequency from Datastream: the S&P 500 excess returns, changes in the 5-year US constant maturity Treasury yield, changes in the CBOE VIX volatility index, changes in the exchange rate relative to USD, country excess stock market returns from MSCI, yearly debt-to-GDP ratios, and yearly credit ratings from Oxford Economics. For the few countries that do not have their own MSCI index, I use the regional MSCI index instead. The European countries Cyprus, Latvia, Malta, Slovakia, and Armenia use the MSCI Emerging Market Index. The local market returns for the Dominican Republic are substituted with the MSCI Frontier Markets Latin America and Caribbean Index. The yearly credit ratings are transformed into five risk buckets for use as a categorical control variable: [0, 4], (4, 8], (8, 12], (12, 16], and (16,20]. Finally, the yearly debt-to-GDP ratio is cubically interpolated to the monthly frequency. The summary statistics for all financial variables used in the research are provided in Table 3.

## 2.2 Attention Index

The predictions outlined in Section 1 posit that greater news attention to climate hazards could influence sovereign CDS equilibrium prices. Heightened attention to climate hazards is already recognized to be a driver of prices in the bond (Painter, 2020), stock (Choi et al., 2020), and housing markets (Giglio et al., 2021). In this context, SLR and coastal flooding risks for affected sovereigns should become increasingly salient to the credit market as news and information are disseminated during international climate summits. To capture the market's awareness of climate vulnerability, which fluctuates over time, an index measuring the content of media articles can be used as an indirect method of pricing these risks.

The reason I highlight international summits is that these events bring global attention to climate risks such as storm surges and SLR, amplifying the reach of climate related information. For example, delegate Naderev Sano held a public hunger strike during the Warsaw Climate Conference to raise awareness of the devastating impact of Hurricane Haiyan on

[8]The spreads of some sovereigns are relatively stable, and the returns therefore contain a large number of zero values.

his representative country and hometown, Tacloban in the Philippines.[9] The 1061 missing, 28,689 injured, and 6,300 dead were largely attributable to the storm surges caused by the cyclone (Lagmay et al., 2015). Another example was when Tuvalu's foreign minister delivered a speech while standing knee-deep in the ocean during the Climate Conference in Glasgow. This striking gesture was meant to emphasize the effects of climate change and SLR on low-lying regions, and the speech was rapidly disseminated throughout the media.[10] Although the events aim to coordinate interventions to address a changing climate, either by way of adaptation or mitigation, greenhouse gas emission reductions pledged by industrialized nations typically fall far short of the reductions needed by 2030 to keep the world within a disruptive 2°C warming scenario Vandyck et al. (2016).

To represent global attention to climate summits, I adopt the news index developed by Faccini et al. (2023). They uncover various factors by performing a textual analysis using Latent Dirichlet Allocation from a corpus of 33,735 news articles pertaining to "climate change" or "global warming" from Reuters. The machine learning method classifies the news corpus into categories dependent on the frequency of set words appearing, as well as the share associated with a given topic. Specifically, I choose the topic related to international climate change summits, illustrated in Figure 1, as it represents events that shift the attention of investors globally. The topic consists of words such as Copenhagen, summit, protocol, Kyoto, and agreement—all words relating to climate summits. Further, Dickey-Fuller tests confirm that the index is stationary, supporting its validity for time-series analysis.

While no news index can perfectly capture the news digested by the financial market, the international summits index has elements making it a strong candidate for this use case. Ardia et al. (2020) uses U.S.-news-based sources such as the Los Angeles Times and the Washington Post to develop their sentiment-based indices. The novel work of Engle et al. (2020) proposes a U.S.-centric metric of climate risk that may capture other irrelevant information. Faccini et al. (2023) use 13 million news articles published by Reuters, a global news agency directly connected to the financial information platform Eikon. The news provider is international and therefore salient for sovereign CDS market participants—fitting the setting of the empirical design. This application also expands the use of the index from the original paper as they only test whether it has relevancy within the U.S. equity market. Furthermore, the climate summit index does not attempt to gauge sentiment as in Ardia et al. (2020); instead, the measure captures the *intensity* of the topic reported for a given period. A sentiment index focuses on the emotional tone conveyed in news articles, aiming to quantify whether the

[9] From the CNN article, "Philippines delegate refuses to eat until action on climate change madness", published on November 12, 2013.

[10] From The Guardian article, "Tuvalu minister to address Cop26 knee deep in water to highlight climate crisis and sea level rise", published on November 8th, 2021.

sentiment expressed is positive, negative, or neutral. Intensity, on the other hand, measures the strength or magnitude of the discussion surrounding international summits.

While Faccini et al. (2023) do not differentiate positive from negative news, I consider increases in the climate summit index as "bad news" due to the general uncertainty and lack of material commitments generated during climate summits (Hsu et al., 2015).[11] Prior literature also find that summits such as the one leading up to the Paris Climate agreement increased credit spreads, suggesting increased risk perception in the CDS market Kölbel et al. (2024). This interpretation aligns with Engle et al. (2020), who expect attention to rise when there is cause for concern, indicating an adverse effect on an economy. One caveat is that these factors capture media attention explicitly, rather than investor attention (Da et al., 2011). An increase in the intensity of climate news does not necessarily mean that investors will read the articles. Nonetheless, there is strong evidence that the level of news coverage is a suitable proxy for the level of attention investors pay to climate change.

## 2.3 Construction of Extreme Sea Level Hazard

Since the first objective of this paper is to understand whether the market incorporates coastal flooding, this section aims to measure exposure in a unsophisticated manner—as it will be more likely to be incorporated into financial markets (Hirshleifer, 2015). I choose to use population as a metric for vulnerability as the approach has been used in other contexts in the economics (Dell et al., 2012) and climate science (McMichael et al., 2020) literature.[12]

To compute the *ESL* hazard for the sample of 59 countries, I use estimates of the percent of total population living in the 1-in-100-year floodplain in the year 2000 according to Vafeidis et al. (2011) and Neumann et al. (2015).[13] These studies undertake a comprehensive assessment of the current and future exposure of land and population to coastal flooding on national and global scales. They generated estimates of the land area and population (as of the 2000 census) within the 1-in-100-year coastal floodplain. To measure the exposure, the authors use storm surge heights from the Dynamic and Interactive Vulnerability Assessment (DIVA) and population data from the Global Rural-Urban Mapping Project (GRUMP). Both databases were widely adopted in order to measure vulnerability to coastal flooding and SLR hazard in the post-2000 period (e.g., Dasgupta et al. (2009)). Moreover, these evaluations gained significant traction and validation in the scientific community, as evidenced by the

[11] Prominent climate scientists, such as James Hansen, have stated that the policies enacted during international summits are inadequate to curb the effects of climate change.

[12] In the economics literature population exposure is also useful as a metric as it has direct implications on aggregate output and labor productivity of the economy.

[13] The estimates of exposure were initially available in 2011 and then later published in an academic journal in 2015.

numerous citations of Neumann et al. (2015).

For this study, I use the exposure metric of a 1-in-100-year flooding event—an incident that has a 1% chance of occurring each year—to assess land vulnerable to coastal flooding, i.e., *ESL* hazard. This return period of flooding is chosen because it is commonly used by climate scientists, such as Hallegatte et al. (2013), and is in turn applied in the finance literature (Painter, 2020). Furthermore, whether a country is protected against flooding is gauged using the 1-in-100-year threshold to determine protection status (Vafeidis et al., 2011). Consequently, I obtain current SLR protection standards for the countries in the sample from Lincke and Hinkel (2018). I set the exposure for Hong Kong, Israel, Italy, Qatar, Bahrain, and the Netherlands to zero as they are protected against such disasters.

This cutting-edge climate analysis from the first decade of the 2000s produces a rich heterogeneity in the sample. Table 2 shows the percentage of each country's population living in the 1-in-100 year floodplain, which I refer to as *ESL* hazard. The table is sorted so that the most vulnerable countries, such as Vietnam, Belgium, and Egypt, are at the top left, with decreasing vulnerability as you move down the table. The right panel is a continuation of the exposure data, also sorted from top to bottom according to exposure. The bottom section of the table includes countries that are protected against these 1-in-100-year coastal floods. I also sort countries into quartiles and quintiles based on their percent of exposure; these can be identified as the second and third column of each panel in Table 2.

For the empirical identification strategy, I use a methodology that sorts sovereigns into "more-" and "less-exposed" groups, rather than relying on raw exposure numbers. This sorting is convenient because, while Table 2 accurately replicates the information available to investors at the time, investors might use alternative data to derive their own exposure estimates for a given sovereign. As a result, sorting proves more effective, as the absolute numbers are less crucial than the relative positioning among countries. This approach aligns with recent climate literature; according to Muis et al. (2017), although absolute exposures have changed between 2004 and 2017, relative rankings have remained largely stable. I provide evidence of this in Section 4.2, showing that using alternative data sources does not dramatically alter the classification of the most exposed sovereigns, specifically those in quartile 4. Essentially, this sorting technique is intended to alleviate concerns of measurement error in the exposure calculation and allows for the differentiation of sovereigns based on vulnerability, rather than on a perfect understanding of the market's perceptions of exposure.

## 2.4 Construction of Changes in Extreme Sea Level Hazard

Next, I measure whether a country's vulnerability to coastal flooding is increasing or decreasing as a result of population growth and sea level rise (SLR)—what I term $\Delta ESL$ hazard. I calculate country-specific trends in vulnerability using two separate methods: (1) evaluating forecasted trends based on SLR and population forecasts developed by Vafeidis et al. (2011) and Neumann et al. (2015) and (2) extrapolating out historical or observed exposure estimates based on data from 2000 to 2010. In this section, I describe how I derive both observed and forecasted $\Delta ESL$ hazards and highlight the substantial differences between them.

I focus on a subset of sovereigns vulnerable to $ESL$ hazards, specifically those in the fourth and fifth quintiles as indicated in Table 2. I select this sample because population growth and SLR will not meaningfully increase vulnerability to coastal flooding unless a country already has a baseline exposure to $ESL$ hazard. Therefore, the first, second, and third quintiles are not included when assessing whether the credit market incorporates $\Delta ESL$ hazard.

The prevailing assumption in early 21st-century research on coastal flooding was that coastal populations would grow more quickly than inland populations (Nicholls et al., 2008). This assumption was based on the rapid population growth observed in the coastal zones of Bangladesh and China and was extrapolated globally. To represent this belief in my empirical analysis, and to maintain consistency with the previous section, I once again utilize data from Vafeidis et al. (2011) and Neumann et al. (2015). Instead of using their baseline exposure estimates for 2000, I use their projections of the percentage of the population exposed under scenario-driven assessments. The projections account for future coastal population exposure, considering narrative scenarios of migration and SLR, as developed by the UK Government's Foresight project.

The projections include sovereign populations exposed to 1-in-100-year coastal flooding over 30-year periods beginning in 2000 under four socio-economic scenarios (A through D), all of which assume faster population growth on the coast than in the interior.[14] The Foresight scenarios A and C anticipate high population growth, while scenarios B and D predict low to medium global population growth. These scenarios also assume a SLR of 10 cm by 2030, which would subsequently expand the area of the 1-in-100-year floodplain and increase the number of people affected.

In order to evaluate whether a sovereign is forecasted to be increasing or decreasing in exposure to coastal flooding, I regresses the yearly percent exposed ($SLRE$) for each sovereign $s$ on a linear time trend $\gamma$ for the year $t$ as follows:

$$SLRE_{s,t} = a_s + \gamma_s t + \epsilon_{s,t}, \tag{4}$$

[14]While more recent literature by Merkens et al. (2016) has corrected this assumption by also accounting for rapid inland population growth, I maintain that the earlier theory was well-accepted by both the scientific community and the credit market.

where the estimated $\gamma$ values represents the rate of change in the percentage of the population exposed per year.

To remain consistent with the prior Section, I use the base year 2000 assessment and the four population projections under the four scenarios available for the year 2030. I then estimate a weighted least squares regression comparable to the regression outlined in Equation 4. Although the Foresight project offers no probability weighting for the scenarios, I assume equal weighting of 0.25 for each of the scenarios. Based on these weightings, I estimate the rate of change in coastal flooding exposure, $\gamma$, for the 23 sovereigns with a baseline vulnerability to *ESL* hazard. Figure 2 illustrates the values of the estimated $\gamma$ coefficients, sorted from least to greatest, when using climate and population forecasts. To mitigate concerns of measurement error, I use a sorting methodology and split sovereigns by the median value of $\gamma$ to obtain the "more-" and "less-exposed" groups. These groups are visualized above and below the black dashed line in Figure 2.

Next, I calculate the observed trends in exposure, given that the credit market may prioritize real data over projections. The observed $\Delta ESL$ is determined using yearly gridded population data from 2000 to 2010 provided by WorldPop and the Global Tide and Surge Reanalysis (GTSR) dataset from Muis et al. (2016) which measures 1-in-100 year flood inundation in centimeters. These datasets are chosen to reflect the information available information to the market before the estimation period. I use the GTSR dataset because access to the original DIVA dataset is now restricted; however, Muis et al. (2017) find that geographic patterns of extreme sea levels in the two datasets show qualitative agreement. The data contains the expected 1-in-100-year flooding extent in the form of a gridded raster file, at a spatial resolution of 30" $\times$ 30" (1 $\times$ 1 km at the equator). Their methodology relies on two hydrodynamic climate models that simulate the rise in water during storm surges and tides. The methods account for wind speed, atmospheric pressure, and elevation, but disregard existing coastal protection structures.

I also use the WorldPop gridded population database, available yearly from 2000 on to 2010, which uses a consistent methodology across time making it useful for time series analysis. This reflects the type of information the market would have had access to if they kept up to date with demographic trends. Archila Bustos et al. (2020) finds that WorldPop performs well compared to other datasets and has lower prediction error and better accuracy than alternatives like LandScan.[15] Using this dataset, I overlay it with the GTSR dataset and apply a minimum threshold of 30 cm as a cutoff to designate a 1 $\times$ 1 km grid as exposed to *ESL* hazard and calculate the percentage of the population exposed in a country. I then

[15] Landscan, for example, changes its methodology every year, making it unsuitable for time series applications.

regress the yearly percentage exposed ($SLRE$) for each sovereign $s$ on a linear time trend $\gamma$ for the years 2000 through 2010. Figure 3 shows the split of countries based on the estimated $\gamma$ values.

As an illustrative example of spatial exposure calculation, I present the logarithmic population distribution of Vietnam in 2010, derived from the WorldPop dataset, in the left panel of Figure 4. This figure indicates a high population density around Ho Chi Minh City. The right panel of Figure 4 depicts the population residing in areas with more than a 30 cm flooding vulnerability threshold, underscoring that a significant portion of Vietnam's population is concentrated in low-lying coastal regions. This methodology is useful in discerning the temporal dynamics of population growth for countries vulnerable to flooding.

This approach allows for the separation of $ESL$ and $\Delta ESL$ hazard, where prior literature typically used global mean sea level rise for their analysis (Goldsmith-Pinkham et al. (2023); Bernstein et al. (2019); Baldauf et al. (2020)) or assumed that historically obtained $\Delta ESL$ is indicative of future exposure (Murfin and Spiegel, 2020). The heterogeneous risk should be reflected in sovereign CDS spreads if investors are aware of climate model projections and the costs of future coastal surge disasters. Leveraging this subtle variation, I investigate whether the credit market correctly distinguishes between countries with decreasing or increasing vulnerability to coastal flooding.

# 3 Empirical Results and Discussion

## 3.1 Sensitivity to Attention

### 3.1.1 Extreme Sea Level Hazard

To test whether the sovereign credit market incorporates $ESL$ hazard with attention, i.e., the first hypothesis, I use sovereign CDS returns to capture changes in market risk. Akin to the definition from Hilscher et al. (2015), monthly percent changes to 1-, 5-, and 10-year credit returns are calculated for each sovereign, $i$, as:

$$R_{i,t+1}^{SCDS} = \frac{\Delta s_{i,t+1}}{s_{i,t}}. \tag{5}$$

To assess the contemporaneous time-series dynamics between global attention ($Attention_t$) and returns, the empirical estimation strategy relies on panel regressions of sovereign CDS returns on explanatory variables with an indicator term, $Exposure$, that denotes whether a country is vulnerable to $ESL$ hazard. Specifically, $Exposure$ is assigned a value of 1 for countries deemed exposed and 0 for those considered less vulnerable. This indicator is subsequently interacted with *Attention* to estimate the relationship between attention and sovereign CDS returns for both exposed and unexposed country cohorts. I include regional clustering to account for serial correlation of the error term within each sovereign and winsorize returns at 1% (Abadie et al., 2017). The estimated regressions follow the format:

$$R_{i,t+1}^{SCDS} = \alpha + \beta_1(Exposure_i \times Attention_t) + \gamma \Delta X_{i,t} + \eta_i + \rho_{i,t_y} + \varepsilon_{i,t}, \tag{6}$$

for country, $i$, at time $t$. Similar to other empirical studies in this field (i.e., Longstaff et al. (2011); Dieckmann and Plank (2012); Augustin et al. (2020) etc.) I use a comprehensive set of base covariates, $\Delta X_{i,t}$, that control for sovereign-specific and global factors that are known to affect sovereign CDS returns. The global covariates are the change in the 5-year constant maturity Treasury yield, the change in CBOE VIX volatility index, the FTSE World Bond Index returns, and the S&P 500 excess returns. The local covariates include the changes in exchange rate of the local currency to USD, changes in foreign currency reserves denominated in USD, local MSCI excess stock returns, MSCI monthly volatility, and changes in debt-to-GDP ratio interpolated from a yearly frequency to monthly. Although I cannot rule out omitted variable bias affecting the estimates, the control variables should account for the bulk of observable economic information material to sovereign CDS spread returns.

As I am interested in assessing whether global news—a variable common to all countries—has a concurrent effect on sovereign risk, I allow for the majority of time-series variation within each sovereign to remain (Dieckmann and Plank, 2012). The variable $\eta_i$ represents country-by-month fixed effects to capture seasonal unobserved country heterogeneity that may affect sovereign CDS spread returns. $\rho_{i,t_y}$ represents a fixed effect obtained by transforming a numerical credit-rating from Oxford Economics and mapping the series into five "risk buckets" that control for the yearly rating of each sovereign. Overall, this specification choice is simply a reparameterization of a fully interacted model in order to highlight the marginal effects of the index on returns, conditional on whether a country is vulnerable to *ESL* hazard, rather than the difference between groups. [16]

In line with hypothesis $H_1$, I expect the marginal effect of *Attention* on returns for the more affected sovereigns to be significantly greater than zero for medium- to long-term sovereign CDS tenors. Moreover, I expect the coefficient of interest, $\beta_1$, to be significantly greater than zero, indicating a difference between exposure groups. For this relationship to hold, market participants must respond to the arrival of information, as proxied by the index, and correctly differentiate between the most and least vulnerable sovereigns. To

[16] A fully interacted model would be $R_{i,t+1}^{SCDS} = \alpha + \beta_1(Exposure_i \times Attention_t) + \beta_2 Attention_t + \gamma \Delta X_{i,t} + \eta_i + \rho_{i,t_y} + \varepsilon_{i,t}$ where $\beta_1$ represents the estimated difference in the effect of *Attention* on returns between the two groups. The country fixed effect subsumes the need for a separate "main effect" for *Exposure*.

approximate the information available to the market and mitigate measurement error in calculating sovereign exposure, I use an identification strategy that relies on sorting. This method exploits the differential exposure to *ESL* hazard found in Table 2 and discussed in detail in Section 2.3.

Specifically, I subset the entire 59 country sample into quartiles of exposure, where the fourth quartile contains the most exposed sovereigns, and the second and first quartiles are the least exposed to *ESL* hazard. This method places the 14 most vulnerable countries into a single "more exposed" category, and the other 30 into the "less exposed" category. I argue that this strategy is reasonable because vulnerability is heavily skewed to the fourth quartile and precipitously falls in the third and second quartiles.[17]

Reverse causation in this regression setting is unlikely to significantly bias the estimates. It is unrealistic to believe that deteriorating sovereign CDS returns for specific sovereigns would prompt countries to organize additional international summits. The only plausible pathway would be if a disastrous coastal surge event occurred in the lead-up to an international summit. Such a catastrophe could cause a short-term negative effect on sovereign CDS returns and may lead to more media articles about the importance of the climate summit. While the news cycle may notice such an event, it is implausible that the disaster would dominate the news during the climate summit.

Table 4 presents the estimates from regressing the 1-, 5-, and 10-year sovereign CDS returns of sovereigns against the attention index. The first two rows produce the marginal effects of the index on returns, conditional on the exposure as measured by the sorting procedure. None of the coefficients in the second row of the Table are significantly different from zero, indicating no relationship between returns and attention for the least affected countries. By comparison, the relationship between the news and the 5- and 10-year returns for the more exposed sample are significant at the 5% and 1% level, respectively. Specifically, the marginal effect of a one-standard-deviation increase in the attention index is associated with a rise of 0.69% and 0.80% in the 5- and 10-year CDS returns of affected sovereigns. The association between attention and the term structure of sovereign CDS spreads is found to be upward sloping, as the increase in the 10-year spread is more economically meaningful than the equivalent increase for the 5-year spread.

Following the regression analysis, I perform post-estimation tests to explicitly determine whether the coefficients for the climate summits' attention index statistically differ between the exposed and unexposed groups. The tests yield t-statistics of 1.81 and 2.57 for the 5- and 10-year sovereign CDS spreads, suggesting a significant difference in the coefficients at

[17] T-tests confirm that the resulting groups do not significantly differ in their sovereign CDS returns over the sample period.

the 10% and 5% levels of significance, respectively.

The magnitude of the relationship can be compared to the empirical results from the no-arbitrage model for the valuation of sovereign CDS contracts developed by Doshi et al. (2017). Specifically, they use the model to differentiate the relationships between common global and local covariates and CDS spreads. In a broad sample of sovereigns from Latin America, Asia, and the Eurozone, they find that a one-percent increase in the unemployment rate results in a 2.9 basis point increase in spreads. Back-of-the-envelope calculations reveal that this is comparable to a 1.77% increase in sovereign spreads with a one-standard-deviation rise in the unemployment rate. The estimates produced in this study are roughly half the effect size of a one-standard-deviation shock to the unemployment rate—indicating a consequential impact on sovereign CDS returns.

Taken together, the findings provide robust evidence that sovereign credit default swap (CDS) returns for ESL-afflicted sovereigns are contemporaneously associated with global attention to climate summits. The estimated coefficients support Hypothesis $H_1$, indicating that the market perceives ESL exposure as a medium- to long-term risk during periods of heightened attention to climate summits.

The results carry broader implications. First, they suggest that investors use the population exposure of sovereigns to differentiate between vulnerable countries, thereby confirming the face validity of this metric. This is a novel finding and adds to other studies that examine other climate phenomena. For instance Dell et al. (2012) utilize a population-weighted temperature metric to examine the decline in economic activity. Second, the findings underscore the pricing of this vulnerability in longer-term CDS tenors, which is reasonable given that the likelihood of experiencing a devastating flood event increases over longer periods. Third, the results demonstrate that heightened news attention increases saliency of climate risk, extending the literature that has found similar outcomes in other assets (see Engle et al. (2020) and Giglio et al. (2021)).

As this result is critical to study the more complex question of whether SLR hazard is incorporated, I perform a set of robustness checks that further confirm these results. In Section 4.1, I use an event study to reveal that sovereigns with greater vulnerability to *ESL* hazards experienced an increase in long-term credit risk during the lead-up to the Paris Agreement—a noteworthy climate summit. Section 4.2 demonstrates that using alternate data from the 2000s yields consistent results. In Section 4.3, I decompose CDS spreads into a risk premium component for each country using the affine sovereign credit risk model of Pan and Singleton (2008) to show that a one-standard deviation increase in attention increases risk premiums by 49 and 59 basis points for 5- and 10-year sovereign CDS spreads. I also establish that the results remain intact after accounting for liquidity (see Section 8.2).

Moving to Section 8.3, I use an alternative country-level attention index—Google Trends data on "UN Climate Change Conferences"—and uncover a similar relationship across medium- and long-term CDS spreads. In Section 8.1, I leverage CDS notional amounts from the Depository Trust and Clearing Corporation to highlight that net protection bought or sold rises in response to news. Finally, in Section 8.5, I show that incorporating additional climate risks leaves the magnitude and direction of the estimated relationship unchanged.

### 3.1.2 Changes in Extreme Sea Level Hazard

In this section, I conduct empirical tests to study whether the credit market is accounting for changes in *ESL* exposure. The goal is to examine whether hypothesis $H_2$ holds for a hazard manifesting over a longer time scale. Consequently, only the 5- and 10-year spreads are selected as the dependent variables, as $\Delta ESL$ is only relevant at these longer timescales.

I use a set of sovereigns that are vulnerable to *ESL* hazards, specifically those in the fourth and fifth quintiles as denoted in Table 2. This sample is chosen because a baseline level of vulnerability is necessary for variations in SLR and population changes to meaningfully impact exposure to coastal flooding. Additionally, expanding the set of sovereigns increases the power of the regressions.

The 23 selected sovereigns are divided into two groups based on their level of exposure: a more- and less-exposed sample. This division is determined by the estimated linear time trends, $\gamma_s$, using either observed data or climate and demographic projections, as outlined in Section 2.4. The two sets of climate data produce drastically different groupings of sovereigns vulnerable to $\Delta ESL$ hazard, as illustrated in Figures 2 and 3. I use a similar estimation strategy as outlined in Specification 6, but include a "main effect" of *Attention* to highlight the difference in the effect of the index on returns between exposure sets.

I present the estimates for the groups of sovereigns that are more- or less-exposed to $\Delta ESL$ hazard in Table 5. Columns (1) and (2) show the estimates from groupings based on forecasts, while columns (3) and (4) are grouped according to $\Delta ESL$ exposure calculated with observed data. The first row shows the effect of the news index on CDS returns for sovereigns at risk of greater coastal flooding damages due to SLR and coastal population growth, in contrast to sovereigns with inland population growth and limited SLR. The absence of a statistically significant difference between the exposure groups in panels (a) and (b) underscores the idea that the market does not price $\Delta ESL$ hazard *contemporaneously* with climate news. This result supports hypothesis $H_2$ in that the hazard is unpriced concurrently with news entering the total mix of information; however, further empirical tests have to be performed in order to see whether there is an underreaction.

In Section 4.3, I perform a robustness check that further confirms the return response pattern I find in this section. Again, I use the decomposed risk premiums for 5- and 10-year sovereign CDS spreads and regress this on the interaction terms. Table 11 shows that there is no significant difference between groups of sovereigns.

The main results presented here use an equally weighted forecast across all four population and SLR scenarios denoted in Neumann et al. (2015). In a robustness check shown in Section 4.2, I confirm that other scenarios are also unaccounted for. Specifically, when considering each of the four scenarios separately, there remains a non-significant difference between the exposure groups.

What types of informational frictions could be causing this result? The observations highlighted in Section 2.4 explicitly show the divergence between the rates of change in exposure calculated using observed versus projected data, concluding that population assumptions made in the early 21st century were incorrect. The disagreement in observed versus forecasted trends could mean that the market is simply averse to the ambiguity of information. Ellsberg (1961) considers a set of paradoxes that outline investors' distaste for ambiguity. In this setting, the uncertainty of each parameter determining future exposure leads to investors depending on observed rather than ambiguous future forecasts. This explanation, however, holds little water since the coefficients in the first row of panel (b) are not significant. Furthermore, the assumption that population growth would burgeon in coastal zones had been an accepted theory, based on with the body of work from McGranahan et al. (2007) until Neumann et al. (2015). Furthermore, assessment of coastal flooding exposure and SLR at the sovereign scale has been relatively static in the cross-section due to the proliferation of the DIVA modeling tool used in population exposure estimates (Muis et al., 2017). Considering the well documented and long-standing scientific consensus on climate and population projections prior to 2016, it is implausible that ambiguity aversion would drive the credit market to not price the hazard.

Another behavioral explanation may be that incorporating climate projections requires specialized knowledge of up-to-date geophysical information, which may be onerous for the market to incorporate. Indeed, investors have limited cognitive resources (Kahneman et al., 1982) and may use heuristic simplification to deal with problems they are unfamiliar with. Investors may also be prone to overlooking long-term signals and demographic changes that are less salient when the information is reported (DellaVigna and Pollet, 2007). In the context of processing observed versus forecast information, the market may simply be neglecting the more complex projections concurrently with elevated attention and incorporating the information in a laggard fashion. This friction would result in a delayed market reaction, in that lagged attention would positively predict the CDS returns for the more vulnerable sovereigns under forecasts. If, instead, return predictability is greater for the more vulnerable sovereigns when using observed data, this would imply that the market continues pricing the less complex but accurate $\Delta ESL$ hazard according to observed trends of population exposure to coastal flooding. In the next Section, I find evidence of the former in that the market gradually impounds information on $\Delta ESL$ from climate and demographic models asynchronously with attention, suggesting the market differentiates between the publicly available data.

These nuanced findings are in line with prior conclusions of Murfin and Spiegel (2020) who find that future property inundation, based on historical data, is not priced in residential real estate markets. The conclusion that sophisticated institutional investors (i.e., CDS traders) incorporate ex-ante climate risk is in line with Nguyen et al. (2022) who uncover an SLR premium and increased default probability for affected residential properties, and with Bernstein et al. (2019) who propose that institutional investors price SLR hazard.

## 3.2 Market Efficiency

I next show that sovereign CDS returns for countries exposed to $ESL$, and particularly $\Delta ESL$ hazard, are highly predictable when using the climate summit news index. This predictability suggests that the market is sluggish in pricing coastal flooding and SLR exposure based on news, supporting hypothesis $H_2$.

### 3.2.1 Predictability

Behavioral theories demand that there is an under- or overreaction to new information in asset prices, leading to a predictability that is inconsistent with the efficient markets hypothesis, as reviewed by Fama (1970). Initially, I use a panel vector autoregression (PVAR) approach, previously used by Lee et al. (2018) and Cathcart et al. (2020), to measure predictability for sovereign spreads that are structured in a panel format. The results, presented in Section 8.4, show that two lags of the attention index are significant in predicting CDS returns. However, in-sample estimates, though useful as a first pass to check for predictability, suffer from look-ahead bias since the estimation uses all available information. Welch and Goyal (2008) instead advocate for out-of-sample regressions as the highest standard for predictability, as they mirror the real-time situation of investors. [18]

Conventionally, predictability has been evaluated on time-series returns, rather than in panel form. The well-known commonality of sovereign CDS spreads (see Longstaff et al. (2011)) makes them suitable for transforming into a time-series format. I use two different

[18] Many studies use OOS predictability as a way of showing that there is easy money to be made, but that is not the aim of this exercise. Instead, the goal is to illustrate the extent of market underreaction to climate information, excluding the examination of potential arbitrage costs.

approaches to collapse the returns for each exposure group on the basis $\Delta ESL$: (i) a simple average and (ii) a principal components analysis (PCA) to identify a single common latent factor that best maintains the covariance structure among each sample.

Both averaging and PCA act as methods to linearly combine the spread returns across the sample. Instead of equally weighting each sovereign, the PCA compresses the estimation of the higher dimensional set of sovereign CDS returns to a common set of latent factors, which are the priced risks across the market. To fix ideas, consider the data matrix of demeaned sovereign CDS returns $X$ for $P$ sovereigns over $T$ time periods, decomposed into three smaller matrices using singular value decomposition (SVD):

$$\underbrace{X}_{T\times P} = \underbrace{U}_{T\times T}\underbrace{S}_{T\times P}\underbrace{V^T}_{P\times P}, \tag{7}$$

where $S$ is a diagonal singular value matrix and both $U$ and $V^T$ are orthonormal. The columns of $V$ contain the factor loadings or eigenvectors of $X^T X$. The first principal component, the vector containing the greatest sample variance for all linear combinations of $X$, is obtained as:

$$z_{t,1} = X v_{t,1}, \tag{8}$$

where $v_{t,1}$ is the first column of matrix $V$. $z_{t,1}$ is calculated for each more- or less-exposed grouping of sovereigns when using either the *ESL* and $\Delta ESL$ measures of hazard. The total variance captured by the first factor ranges from 49% to 59% across each sample. In comparison, Longstaff et al. (2011) find that a single principal component of their sample represents 64% of the total variation in the market.

The OOS regressions are estimated using the summation of sovereigns across time, $\frac{1}{n}\sum_{i,t}^{n} R_{i,t}^{SCDS}$, or the first principal component, $z_{t,1}$, as the predicted variables. I use the second-period lag of the climate summit attention index as the predictor variable as the results in Section 8.4 indicate substantial in-sample predictability up to the second lag. To test the degree of OOS predictability, I use the $R^2_{\mathrm{OS}}$ of Campbell and Thompson (2008) that compares the mean squared forecast error (MSFE) between the estimates obtained using the predictors, and a naive benchmark that assumes no predictability. The statistic can be outlined as follows:

$$R^2_{\mathrm{OS}} = 1 - \frac{\sum_{t=T_1}^{T}\left(r_t - \hat{r}_{\mathrm{t}|t-2}\right)^2}{\sum_{t=T_1}^{T}\left(r_t - \bar{r}_{\mathrm{t}|t-1}\right)^2}, \tag{9}$$

where $\bar{r}_t$ is the historical average return computed based on data through $t-1$, and $\hat{r}_t$ is the fitted value estimated using the predictive regression through $t-2$. $T1$ represents the first observation in the out-of-sample period used for forecast evaluation. While OOS predictability tests are infrequently performed for sovereign CDS returns, I use the shorthand by Campbell and Thompson (2008) who argue that an $R^2_{\mathrm{OS}}$ greater than 0.5% represents an economically valuable predictor.

I present the $R^2_{\mathrm{OS}}$ values obtained from rolling windows of 48 and 54 months in Table 6. Columns (1) through (4) represent the groups of sovereigns split according to $\Delta ESL$ hazard. Each row contains information on which rolling window was used, as well as the predicted variable—either average returns or the first principal component of each group. I test the statistical significance of the $R^2_{\mathrm{OS}}$ values by assessing whether the MSFE of the predictive model exceeds the rolling average, using the Clark and West (2007) test with Newey-West standard errors.

Across all columns, return predictability is greatest for the group of sovereigns with higher exposure to $\Delta ESL$ hazard based on forecasted demographic and climate information, as shown in column (4). The $R^2_{\mathrm{OS}}$ statistics are economically meaningful, ranging from 2 to 3, and are significant at the 5% level within the rolling windows of 48 and 54 months. In contrast, the OOS tests for the sovereigns grouped by observed trends in column (4) show no economically meaningful $R^2_{\mathrm{OS}}$ values and no significant predictability.

These results imply that the market is gradually trading on projected rather than observed data. This finding supports hypothesis $H_2$ and aligns with the results of Chang et al. (2022) and Cathcart et al. (2020), who observe that the sovereign credit market is slow to incorporate new information. This underreaction is consistent with the model of Barberis et al. (1998), which outlines the limited attention of investors when public information is released. More specifically, the results align with the theoretical model and findings of DellaVigna and Pollet (2007), who identify market inattention to demographic trends relevant for the future.

What do these results suggest when taken together with the contemporaneous regressions in Sections 3.1.2 and 3.1.1? As information flows into the credit market, investors incorporate information on coastal flooding exposure which is simpler to process than incorporating more complex climate and population projections. Then, in the following months, the market prices $\Delta ESL$ risk and slowly incorporates the relevant information—suggestive of an initial underreaction supporting hypothesis $H_2$ (Simon, 1956).

To contextualize the results in terms of the prior literature, I uncover an explanation for the underreaction found in Hong et al. (2019), specifically, I find that inattention to news is mechanism in which markets underreact to climate change hazards. I also find that they coincide with those of Schlenker and Taylor (2021) in that the credit market eventually assimilates climate trends. However, a crucial observation made in Schlenker and Taylor (2021) is that projections of temperature trends have generally been accurate. In contrast, forecasts of populations exposed to 1-in-100-year coastal flooding events have been inexact for many sovereigns in comparison to their observed values as outlined in Section 2.4. This discrepancy suggests that the market incorporates misleading projection information—ultimately *mispricing* $\Delta ESL$ hazard. If instead predictability had been considerably greater and positive in column (4) than column (2) in Table 6, then this could have been interpreted as the market pricing of the hazard derived from observed trends.

# 4 Auxiliary Empirical Tests

## 4.1 Paris Agreement Shock

The disadvantage of using an attention index to price assets is that each index can be constructed using different corpora or methodologies, leading to varied series across the literature. To circumvent this limitation, I examine the shock induced by the 2015 Paris Agreement, an event acknowledged for its significance in the pricing of corporate CDS spreads and various other financial assets (see Ilhan et al. (2021) and Kölbel et al. (2024)). Using an event study methodology with principal components analysis, I find that the increased media attention in the lead-up to COP21 in Paris is positively associated with abnormal sovereign CDS returns for sovereigns exposed to $ESL$ hazard.

For the event study methodology, I assume that sovereign CDS returns follow an approximate linear factor structure with static loadings. With similar notation to the SVD formulation, outlined in Section 3.2.1, I assume CDS returns for a panel of sovereign can be explained by a latent factor model. I use weekly rather than monthly sovereign CDS returns in order to estimate the factor sensitivities and intercepts, because the lower frequency would offer too few observations to estimate a stable $\beta$. I estimate a common latent factor for each group of sovereigns (unexposed and exposed to $ESL$ hazard) between January 2010 and December 2017. This factor explains 42% of the variance for the unexposed sample and 56% for the exposed sample, respectively.

The time period selected for estimating $\beta$'s is from 24 to 208 weeks prior to the event date—the week ending October 29, 2015. I select this week as the event data point because the result of the Bonn Climate Change Conference had produced a draft of the Paris Agreement, slightly more than a month before the Paris summit.[19] The number of news articles discussing the upcoming climate summit increased dramatically during this period, which suggests greater investor attention as well. During the lead-up to the conference, news

[19] See `https://web.archive.org/web/20160123014706/https://unfccc.int/meetings/bonn_oct_2015/meeting/8924.php`

agencies published articles focusing on the conference, whether signatories would agree on the document, and about climate science.

Sovereign CDS returns are then projected onto the common latent factors during the historical estimation period to obtain sovereign-specific estimates of $\alpha_i$ and $\beta_i$. Abnormal returns are then calculated by subtracting realized returns during the event window by expected returns as follows:

$$AR_{\mathrm{i,t}} = R_{i,t}^{SCDS} - \left(\alpha_{\mathrm{i}} + \beta_{1,\mathrm{i}} f_{1,\mathrm{t}}\right), \tag{10}$$

where $f_1$ represents the first principal component, $\beta_{1,\mathrm{i}}$ is the estimated coefficient from the historical period, and $AR_{\mathrm{i,t}}$ is the abnormal return for a time period in the event window.

Figures 6 and 7 illustrate the cumulative abnormal sovereign CDS returns over a [-4,10] week window for the most and least exposed sovereigns, respectively. Cumulative abnormal returns significantly increase by 1.3% six weeks after October 29, peaking in the last week of COP21. The economic magnitude of the relationship is in line with the prior findings that showed a 80 basis point increase in spreads with a standard deviation rise in the attention index. This result underscores that climate summits do indeed shift the credit market to incorporate coastal flooding risk. In comparison, there appears to be no discernible change in credit risk for the sovereigns less exposed to *ESL* hazard.

The results are generally consistent with Kölbel et al. (2024) in that COP21 increased credit spreads, but I interpret the relationship as indicative of investors perceiving a physical rather than a transition risk. Furthermore, the results have the added implication that climate summits are overall "bad news" for the economy, since they raise awareness of risks but fail to inadequately address climate concerns (Hsu et al., 2015).

## 4.2 Alternative Exposure Data and Sorts

An assumption for this study is that the credit market is generally aware of the vulnerability of sovereigns to extreme sea level rise; nonetheless, it is impossible perfectly discern the exact information set conditioning the market. Therefore, I sort sovereigns based on variation in $ESL$ and $\Delta ESL$ hazard exposure to use as my primary identification strategy instead of relying on specific numerical values of population exposure. Of course, this methodology could still be problematic if the data sources I use are significantly different than the information set available to the credit market. Thus, in this section, I show that the sorting methodology and results are robust to alternative sources and other data processing choices.

To measure *ESL* hazard in Section 2.3, I use publicly available information from before the estimation period (2010), based on assessments of coastal population exposure developed by the UK Government's Foresight project (Vafeidis et al., 2011). Next, I sort the 59 countries in my sample based on this vulnerability and choose the top quartile of exposure as the more exposed sample, denoted in panel a of Table 2. To verify if sorting has resulted in a similar set of vulnerable sovereigns as identified by new methodologies measuring population exposure, I examine other sources of exposure information.

A common methodology for assessing global and national population exposure to extreme sea levels involves using digital elevation models (DEMs) to measure the extent of low-lying land areas. The NASA Shuttle Radar Topography Mission (SRTM), the first global dataset available post-2000 for spatial elevation measurements, has been widely used for this purpose. Kulp and Strauss (2019) uses the SRTM along with a 2010 population dataset to measure the percentage of the population vulnerable to 1-year flooding events. Using a similar sorting methodology for a sample of 59 countries, I list the 14 most exposed sovereigns in panel (B) of Table 7. In each panel in the Table, the countries are sorted from left to right based on the percent of their population that is vulnerable to $ESL$ hazard. The results show minimal differences between the sample of vulnerable sovereigns identified by my methodology (in panel (A) of Table 7) and those identified by Kulp and Strauss (2019).

In panel (C) of Table 7, I include another DEM model developed by the Japan Aerospace Exploration Agency (JAXA) in 2016. The JAXA model uses a different approach to measure elevation compared to the SRTM, specifically employing stereo optical satellite imagery. While the specific rankings of sovereigns are somewhat different, the overall group remains relatively unchanged when compared to the original sort in panel (A) of Table 7.

Overall, this exercise shows that the sorting methodology produces relatively stable groups of exposure even when using different data sources—mimicking the available information that investors had at the time. In Table 8, I test whether the relationship between attention and credit risk remains for the sovereigns vulnerable to $ESL$ according to the marginally changed exposure sorts. Similar to the results in Section 3.1.1, I find a significant positive relationship between attention to climate summits and returns for 5- and 10-year sovereign CDS spreads. Together, these results indicate the robustness of the sorting methodology used to capture vulnerability to $ESL$ hazard.

Lastly, I consider alternative scenarios used to measure $\Delta ESL$ hazard. In Section 2.4, I choose to equally weight socio-economic scenarios A, B, C, and D from the Foresight Project. To demonstrate that the credit market does not contemporaneously differentiate between sovereigns more or less vulnerable to $\Delta ESL$ hazard with news under different forecasts, I test each scenario separately. Using a similar methodology to the one outlined in Section 2.4, I obtain a linear trend estimate to measure whether a country's exposure is forecasted to increase or decrease under each scenario. The first row of Table 9 shows that the main result in Section 3.1.2—that the credit market does not contemporaneously differentiate between sovereigns more or less vulnerable to $\Delta ESL$ hazard—remains unchanged. None of the coefficients in the first row are significant, indicating no distinction between groups.

## 4.3 Risk Premium Decomposition

The finding that there is a significant association between attention to climate summits and pricing of coastal flooding hazard raises the question of whether the market perceives the threat as a systematic risk. To investigate whether the credit spreads of exposed sovereigns command a risk premium during periods of elevated attention, I use the reduced-form model of Pan and Singleton (2008) and Longstaff et al. (2011) to decompose the term structure of spreads into a "distress" risk premium. This premium captures the unpredictable variation in the arrival rate of a credit event or, in other words, the market's perception of default risk. Intuitively, the risk premium is the additional return required by a risk-averse investor over that of a risk-neutral investor. I expect risk premiums to be positively associated with attention for longer maturities, in line with hypothesis $H_1$ and the prior results.

The affine model put forth by Pan and Singleton (2008) is to identify the arrival rate of a credit event or risk-neutral intensity of default, $\lambda$, which evolves stochastically and is time varying. This model assumes that the time of default, $\tau$, for a sovereign is characterized by the first jump of a doubly stochastic Cox process (Lando, 1998). As described in the Hypothesis Development section, the approximate valuation for newly written sovereign CDS insurance contracts at maturity M is:

$$SCDS_t(M) \approx \lambda_t(1 - R^Q), \tag{11}$$

for time $t$. Here, $R^Q$ is the constant fractional recovery on the cheapest-to-deliver bond if a credit incident occurs. The $Q$ superscript represents the default process under a risk-neutral measure or, put differently, the discounted cash flow of the bond (Duffie, 2005). The main idea is that the unpredictable variation in the market sovereign CDS spread is proportional to the time-varying but unpredictable variation of the risk premium, $\lambda$. After estimating the risk premiums for each sovereign, more thoroughly discussed in Appendix A, I winsorize the estimated risk premium returns at the 1%. I then conduct a similar style of panel regressions as outlined in equation 6.

Table 10 displays the estimates of the risk premium returns of *ESL*-exposed sovereigns regressed on the attention index. The coefficient on the international summits index for the 5- and 10-year returns is positive and significant at the 10% and 5% level for the more exposed sample in columns (2) and (3). The results confirm that coastal flooding is priced as a systematic risk factor into the credit market during periods of heightened news attention. Additionally, the market applies a long-term risk premium for sovereigns exposed to $ESL$ and do not account for $\Delta ESL$ hazards contemporaneously with news.

The regression results for the 5- and 10-year risk premium returns for $\Delta ESL$-exposed sovereigns is found in Table 11. These results reveal a similar relationship to that uncovered in Section 3.1.2, that the market does not differentiate between observed and projected trends concurrently with news.

## 4.4 Protected Countries

The prior results demonstrate that investors are insuring against and therefore pricing $ESL$ exposure. In each test, countries that are currently protected against 1-in-100-year surge events are placed in the less-exposed group. As a robustness check, I empirically test whether countries that have constructed infrastructure to protect against coastal flooding and SLR. These adaptation projects are costly and typically require years to build. For example, the Delta Works project in the Netherlands has taken four decades and $13 billion to complete.[20] The expectation is that credit risk should not increase for countries that have built levees or dikes, thereby leaving the sovereign CDS spreads unaffected.

I select the countries from the sample of 59 that have protection built for 1-in-100-year surges, using the data provided by Lincke and Hinkel (2018). The six remaining sovereign CDS spreads are for Hong Kong, Israel, Italy, Qatar, Bahrain, and the Netherlands. Similar to equation 6, I focus on global attention indices as the time-varying independent variable, with both local and global financial risk factors as controls. The results of the regressions on the 1-, 5-, and 10- year sovereign CDS spreads of protected countries are presented in Table 12. The three columns demonstrate that the index is not significantly related to the sovereign CDS returns of the protected sovereigns, suggesting that heightened global attention does not lead investors to insure against countries that are reasonably protected.

Next, I perform a similar analysis but using the decomposed return premiums as the dependent variable. Table 13 displays nearly identical results to the regressions with sovereign CDS returns, with the added caveat that the coefficients for the attention index in columns (3) and (4) are near zero. The results indicate, across all specifications, that risk premiums are not significantly related to rising attention. This evidence suggests that investors are correctly accounting for $ESL$ hazard while respecting country protection standards. Market participants are therefore rewarding countries that have invested heavily in adaptation to coastal flooding.

[20]From the New York Times article, "Lessons for U.S. From a Flood-Prone Land", published on November 14, 2012.

# 5 Conclusion

In this paper, I show that the sovereign credit market reacts negatively to news surrounding international climate summits by increasing the overall credit risk for countries vulnerable to coastal flooding. Specifically, I use data on exposure to provide evidence that the CDS returns for inundated sovereigns are increasing in comparison to less vulnerable nations when attention to climate summits rise.

I find that the market also prices future exposure of sovereigns based on climate forecasts of population growth and sea level rise. However, this pricing occurs gradually, indicating the presence of market frictions in incorporating valuable climate information. Specifically, the returns on credit spreads for sovereigns exposed to changes in extreme sea level hazards are highly predictable when using an news index that proxies for attention on climate summits.

These results are consistent with a behavioral inattention hypothesis, where investors underreact to important long-term information and only gradually incorporate forward-looking projections from climate science. In this context, incorporating data from climate models presents a substantial challenge for investors, who face limitations in processing capacity and thus struggle to evaluate risks in the distant future. Although the market eventually incorporates climate and demographic forecasts, I find that assumptions about demographic growth made in the early 2000s are inconsistent with observed population data. This observation implies that the credit market misprices the changing vulnerability of sovereigns to coastal flooding.

The results have substantial implications for policymakers and researchers. First, countries exposed to SLR will be compelled to build resilient infrastructure with public finance such as government bonds. However, as sovereign risk increases with the perception of coastal flooding, issuing government debt will become more expensive. Both factors will place undue pressure on the finances of highly affected countries. Second, markets seem to react to climate forecasts, highlighting the need for distributing accurate and up-to-date information. Last, as a cautionary note, climate finance research often uses news indices to price slow-moving climate hazards, which are normally difficult to identify. Given the complexity of processing climate information, this approach could result in overreaction, underreaction, or disregard of essential details. Researchers should therefore seek a deeper understanding of the behavioral implications associated with the news indices they use.

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# 6 Tables

Table 1: Glossary

| **Term** | **Description** |
|---|---|
| SCDS | Sovereign credit default swap. |
| SLR | Sea level rise. |
| *ESL* hazard | The percent of a region that is vulnerable to 1-in-100 year coastal flooding events for the year 2000. A 1-in-100 year flooding event can be described as an event that has a 1% chance of occurring each year. The data for this analysis is gathered from Vafeidis et al. (2011) who use storm surge heights from the Dynamic and Interactive Vulnerability Assessment database and population estimates from the Global Rural-Urban Mapping Project. |
| $\Delta ESL$ hazard | Measures the rate of change in exposure to *ESL* hazard. This is obtained by regressing the yearly percent of a sovereign population vulnerable to 1-in-100-year floods onto a linear time trend. The estimated coefficient attached to the time trend measures whether the sovereign is increasing or decreasing in exposure over time. |
| International summits | This index, developed by Faccini et al. (2023), captures media attention to international climate summits. They use Latent Dirichlet Allocation on Refinitiv Newswires to dissect each article into topics, one of which is international climate summits. |
| Net notional | Aggregate net notional amount of CDS outstanding which is the net sum of CDS insurance bought (or sold) for all contracts. This is in millions of US dollar equivalents using foreign exchange rates and is obtained from the Depository Trust and Clearing Corporation. |

Table 2: Percent of sovereign population exposed to extreme sea level hazard

| Sovereign | % Exposed | Quintile | Quartile | Sovereign | % Exposed | Quintile | Quartile |
|---|---|---|---|---|---|---|---|
| Vietnam | 33.38 | 5 | 4 | Poland | 1.40 | 3 | 2 |
| Belgium | 17.70 | 5 | 4 | Brazil | 1.20 | 3 | 2 |
| Egypt | 10.89 | 5 | 4 | Croatia | 1.18 | 3 | 2 |
| Denmark | 8.84 | 5 | 4 | Russia | 0.94 | 3 | 2 |
| Latvia | 8.06 | 5 | 4 | Romania | 0.87 | 3 | 2 |
| Japan | 6.60 | 5 | 4 | Mexico | 0.76 | 2 | 2 |
| United Kingdom | 6.44 | 5 | 4 | Turkey | 0.73 | 2 | 2 |
| Thailand | 5.50 | 5 | 4 | El Salvador | 0.64 | 2 | 2 |
| China | 4.41 | 5 | 4 | Peru | 0.59 | 2 | 2 |
| Uruguay | 3.94 | 5 | 4 | CostaRica | 0.53 | 2 | 2 |
| Germany | 3.80 | 5 | 4 | Bulgaria | 0.48 | 2 | 2 |
| Norway | 3.34 | 4 | 4 | Slovenia | 0.45 | 2 | 2 |
| Spain | 3.22 | 4 | 4 | Chile | 0.38 | 2 | 2 |
| Ireland | 3.18 | 4 | 4 | Dominican R. | 0.33 | 2 | 2 |
| Morocco | 2.76 | 4 | 3 | Colombia | 0.29 | 2 | 1 |
| France | 2.76 | 4 | 3 | Guatemala | 0.14 | 2 | 1 |
| Korean Republic | 2.73 | 4 | 3 | South Africa | 0.11 | 2 | 1 |
| Philippines | 2.57 | 4 | 3 | Serbia | 0.03 | 1 | 1 |
| Indonesia | 2.55 | 4 | 3 | Slovakia | 0.00 | 1 | 1 |
| Australia | 2.48 | 4 | 3 | Kazakhstan | 0.00 | 1 | 1 |
| Lebanon | 2.41 | 4 | 3 | Austria | 0.00 | 1 | 1 |
| Lithuania | 2.37 | 4 | 3 | Hungary | 0.00 | 1 | 1 |
| Portugal | 2.23 | 4 | 3 | Czech Republic | 0.00 | 1 | 1 |
| Cyprus | 2.21 | 3 | 3 | *Protected Against 1-in-100 Year Floods* | | | |
| Jamaica | 2.19 | 3 | 3 | Qatar | 0.00 | 1 | 1 |
| Panama | 2.06 | 3 | 3 | Italy | 0.00 | 1 | 1 |
| Malaysia | 1.90 | 3 | 3 | Israel | 0.00 | 1 | 1 |
| Sweden | 1.62 | 3 | 3 | Netherlands | 0.00 | 1 | 1 |
| Finland | 1.47 | 3 | 3 | Hong Kong | 0.00 | 1 | 1 |
| Estonia | 1.46 | 3 | 2 | Bahrain | 0.00 | 1 | 1 |

This table shows the percentage of a nation's population residing in the 1-in-100 year coastal floodplain, based on data from the 2000 census—what I call extreme sea level (*ESL*) hazard. The table is sorted so that the most vulnerable countries, such as Vietnam, Belgium, and Egypt, are at the top left, with decreasing vulnerability as you move down the table. The right panel is a continuation of the exposure data, also sorted from top to bottom according to exposure. A 1-in-100 year flooding event can be described as an event that has a 1% chance of occurring each year. The data for this analysis is gathered from Vafeidis et al. (2011) who use storm surge heights from the Dynamic and Interactive Vulnerability Assessment database and population estimates from the Global Rural-Urban Mapping Project. I set exposure to zero for countries with 1-in-100 year surge protection standards according to Lincke and Hinkel (2018). These "protected regions" are visible in the bottom right hand corner of the table. The two rightmost columns of both panels represent the quartile and quintile of exposure to *ESL* hazard, respectively.

Table 3: Sample Statistics

| | Mean | SD | p25 | p50 | p75 | N |
|---|---|---|---|---|---|---|
| % Δ 1 Year Sovereign Spread | 3.538 | 38.223 | -14.459 | -0.276 | 12.998 | 7,021 |
| % Δ 5 Year Sovereign Spread | 0.159 | 13.273 | -7.03 | -0.469 | 4.825 | 7,021 |
| % Δ 10 Year Sovereign Spread | 0.177 | 10.498 | -5.114 | -0.405 | 3.624 | 7,021 |
| MSCI Local Returns | 0.135 | 6.437 | -3.538 | 0.045 | 3.884 | 7,015 |
| MSCI Vol | 7.556 | 47.937 | -22.192 | -1.629 | 24.616 | 7,015 |
| % Δ International Currency Reserves | 18.372 | 1,494.62 | -1.291 | 0.209 | 1.901 | 7,021 |
| % Δ Exchange Rate Dollar | 0.286 | 2.286 | -0.678 | 0.001 | 1.075 | 7,021 |
| % Δ Debt to GDP | 0.303 | 1.412 | -0.202 | 0.169 | 0.674 | 7,021 |
| 1 Year CDS Gamma | -0.048 | 0.24 | -0.196 | -0.04 | 0.107 | 7,021 |
| 5 Year CDS Gamma | -0.019 | 0.243 | -0.165 | -0.013 | 0.145 | 7,021 |
| 10 Year CDS Gamma | -0.029 | 0.244 | -0.172 | -0.02 | 0.132 | 7,021 |
| Google Trends | 2.621 | -7.285 | 0 | 0 | 3 | 6,844 |
| % Δ Log Gross Notional Amount | -0.533 | 6.542 | -3.507 | -0.589 | 2.157 | 3,545 |
| Oxford Economics Credit Rating | 13.379 | 4.287 | 10.5 | 12.667 | 16.667 | 590 |
| NDGAIN Exposure | 0.471 | 0.077 | 0.405 | 0.465 | 0.527 | 580 |
| NDGAIN Infrastructure | 0.282 | 0.102 | 0.207 | 0.279 | 0.344 | 580 |
| NDGAIN Readiness | 0.517 | 0.133 | 0.406 | 0.504 | 0.609 | 580 |
| % Δ VIX | 1.971 | -24.552 | -14.601 | -2.269 | 10.851 | 118 |
| % Δ 5 Yr Treasury | 0.307 | -11.68 | -6.637 | 0 | 5.789 | 118 |
| % Δ FTSE Bond Index | 0.164 | -1.547 | -0.921 | 0.185 | 1.296 | 118 |
| SPX Returns | 0.978 | -3.598 | -0.75 | 1.395 | 3.03 | 118 |
| International Summits | 0.289 | -0.183 | 0.138 | 0.256 | 0.404 | 118 |

This table presents the summary statistics of the variables used in the empirical exercises. Debt-to-GDP is obtained at the yearly frequency but interpolated cubically to the monthly frequency. The credit rating from Oxford Economics is obtained at the yearly frequency and is in the range 0 through 20. The majority of the financial and economic data is obtained through Refinitiv. Weekly net notional amounts which was accessed through historical access to the Depository Trust and Clearing Corporation website Depository. NG-Gain is indices are obtained from the Notre Dame Global Adaptation Initiative. CDS Gamma represents the illiquidity measure calculated in line with Bao et al. (2011). Google trends is the country specific search volume index on the topic “United Nations Climate Change Conference”. The total sample includes 59 countries for the period from January 2010 through November 2019. However, calculating the percent change reduces the estimation sample to start from February 2010.

Table 4: Marginal effects of news on sovereign CDS returns conditional on exposure to extreme sea level hazards

| | (1) 1 Yr | (2) 5 Yr | (3) 10 Yr |
|---|---|---|---|
| More Exposed × International Summits | 3.694 | 3.839** | 4.441*** |
| | (3.160) | (1.757) | (1.399) |
| Less Exposed × International Summits | 1.502 | 0.407 | 0.412 |
| | (1.810) | (0.929) | (0.830) |
| SPX Returns | -1.576*** | -0.840*** | -0.674*** |
| | (0.186) | (0.075) | (0.063) |
| MSCI Local Returns | -1.132*** | -0.518*** | -0.382*** |
| | (0.150) | (0.065) | (0.049) |
| Debt to GDP | -0.034 | 0.022 | 0.009 |
| | (0.140) | (0.105) | (0.076) |
| MSCI Vol | 0.024*** | 0.012*** | 0.009*** |
| | (0.009) | (0.004) | (0.003) |
| FTSE Bond Index | -1.058*** | -0.458*** | -0.392*** |
| | (0.321) | (0.115) | (0.100) |
| Exchange Rate Dollar | 0.310 | 0.331** | 0.213* |
| | (0.265) | (0.160) | (0.119) |
| Intl Reserves | -0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) |
| 5 Yr Treasury | 0.093** | 0.015 | -0.006 |
| | (0.037) | (0.012) | (0.010) |
| VIX | -0.021 | -0.009 | -0.010* |
| | (0.024) | (0.008) | (0.006) |
| SovereignxMonth | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes |
| Adj R Squared | 0.307 | 0.381 | 0.355 |
| Observations | 5088 | 5094 | 5086 |

This table presents regression results linking climate change news related to international summits with sovereign CDS returns at 1-, 5-, and 10-year maturities for countries at risk from extreme sea level (ESL) hazards. The coefficients in the first two rows show the marginal effects of the news index on returns, conditional on sovereigns being more or less exposed to the hazard. "More Exposed" refers to the group of sovereigns in the fourth quartile of Table 4, and "Less Exposed" refers to those in the first and second quartiles. ESL hazard exposure is gathered from Vafeidis et al. (2011) by calculating percentage of a population at risk from 1-in-100 year coastal floods for the year 2000. The $InternationalSummits$ index from Faccini et al. (2023) measures media attention to climate summits. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. All models include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The table reports regression coefficients of sovereign CDS returns, multiplied by 100, for the 1-, 5-, and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

Table 5: Differential effect of news on sovereign CDS returns by exposure to changes in extreme sea level hazard

| | Forecasted $\Delta ESL$ (a) | | Observed $\Delta ESL$ (b) | |
|---|---|---|---|---|
| | (1) 5 Yr | (2) 10 Yr | (3) 5 Yr | (4) 10 Yr |
| Exposed × International Summits | -3.823 | -2.970 | -3.262 | -2.869 |
| | (2.514) | (2.117) | (2.592) | (2.154) |
| International Summits | 4.744** | 4.656** | 4.452** | 4.590** |
| | (2.156) | (1.801) | (2.073) | (1.656) |
| SPX Returns | -0.894*** | -0.742*** | -0.894*** | -0.742*** |
| | (0.104) | (0.074) | (0.105) | (0.074) |
| MSCI Local Returns | -0.685*** | -0.492*** | -0.684*** | -0.491*** |
| | (0.090) | (0.065) | (0.091) | (0.065) |
| Debt to GDP | 0.028 | -0.069 | 0.052 | -0.050 |
| | (0.413) | (0.363) | (0.428) | (0.377) |
| MSCI Vol | 0.021*** | 0.011** | 0.021*** | 0.011** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| FTSE Bond Index | -0.111 | -0.037 | -0.111 | -0.036 |
| | (0.211) | (0.170) | (0.211) | (0.170) |
| Exchange Rate Dollar | 0.056 | 0.027 | 0.062 | 0.032 |
| | (0.201) | (0.137) | (0.198) | (0.135) |
| Intl Reserves | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 5 Yr Treasury | 0.025 | 0.001 | 0.025 | 0.001 |
| | (0.018) | (0.015) | (0.018) | (0.015) |
| VIX | -0.015 | -0.020** | -0.015 | -0.020** |
| | (0.013) | (0.008) | (0.013) | (0.008) |
| SovereignxMonth | Yes | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes | Yes |
| Adj R Squared | 0.284 | 0.250 | 0.284 | 0.250 |
| Observations | 2660 | 2660 | 2660 | 2660 |

This table shows coefficients from a model linking news on international climate summits to 5- and 10-year sovereign CDS returns for countries vulnerable to changes in extreme sea level hazard. The $InternationalSummits$ index from Faccini et al. (2023) measures media attention to climate summits and is interacted with *Exposed* to produce the first-row coefficients, indicating the differential impact on CDS spreads between exposure groups. To calculate $\Delta ESL$, I begin with the 23 most exposed sovereigns to coastal flooding (fourth and fifth quintiles, Table 4). For panel (a), $\Delta ESL$ is derived by regressing the forecasted percentage of the population exposed to 1-in-100 year coastal floods on a linear time trend. Population and SLR forecasts come from Vafeidis et al. (2011). For panel (b), $\Delta ESL$ is calculated similarly but uses observed population exposure data from 2000-2010. Sovereigns are split into more exposed (1) and less exposed (0) groups, represented by *Exposed*, based on whether a sovereign's trend coefficient is above or below the median across the 23 sovereigns. Splits are shown in Figures 2 and 3. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. I include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The coefficients of sovereign CDS returns are multiplied by 100, for the 5- and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

Table 6: $R^2_{OS}$ Out-of-sample predictability of CDS returns

| | | Forecasted $\Delta ESL$ (a) | | Observed $\Delta ESL$ (b) | |
|---|---|---|---|---|---|
| | Rolling Months | (1) Less Exposed | (2) More Exposed | (3) Less Exposed | (4) More Exposed |
| Average Returns | 48 | -5.902 | 3.302** | -5.444 | -0.422 |
| Principal Component | 48 | -5.417 | 3.594** | -5.221 | -0.352 |
| Average Returns | 54 | -6.470 | 2.803** | -5.587 | -0.464 |
| Principal Component | 54 | -5.682 | 3.226** | -5.180 | -0.189 |
| Number of Countries | | 12 | 11 | 12 | 11 |

This table presents out-of-sample return predictability results using the second lag of the climate summit news index as the predictor and a time-series of sovereign CDS returns as the predicted variable. The values presented in columns (1) through (4) are the $R^2_{\mathrm{OS}}$ developed by Campbell and Thompson (2008). The $R^2_{\mathrm{OS}}$ values are calculated based on the rolling months as described in the column titled "Rolling Months". The sample of sovereigns in panels (a) and (b) consist of the of the 23 sovereigns more exposed to *ESL* hazard, described as the fifth and fourth quintiles in Table 4. For panel (a), the changes in *ESL* hazard are approximated by the coefficient obtained from regressing the forecasted (from Vafeidis et al. (2011)) percent of population exposed to 1-in-100 year coastal floods on a linear time trend. For panel (b), the changes in *ESL* hazard are approximated by the coefficient obtained from regressing the observed (2000 to 2010) percent of population exposed to floods on a linear time trend. Then, for each panel (a) and (b), the sovereigns are split into less and more exposed groups by dividing the estimated coefficients by their median value, denoted in Figures 2 and 3. The panel CDS returns for each group of sovereigns are linearly combined to a time-series by either using averaging or the extracting the first principal component. Statistical significance is calculated with the method outlined in Clark and West (2007) using Newey-West standard errors with two lags as the considered autocorrelation structure. Significance is denoted by ***, **, * at the 1%, 5%, and 10% levels, respectively.

Table 7: Sovereigns more exposed to extreme sea level rise hazard according to various data sources

| | | |
|---|---|---|
| *Panel A.* Vafeidis et al. (2011) & Neumann et al. (2015) | | |
| Vietnam | Belgium | Egypt |
| Denmark | Latvia | Japan |
| United Kingdom | Thailand | China |
| Uruguay | Germany | Norway |
| Spain | Ireland | |
| *Panel B.* Shuttle Radar Topography Mission (SRTM) | | |
| Vietnam | Japan | Denmark |
| Belgium | United Kingdom | China |
| Indonesia | Denmark | France |
| Philippines | Ireland | Latvia |
| Thailand | Malaysia | |
| *Panel C.* JAXA | | |
| Vietnam | Denmark | Japan |
| Belgium | China | United Kingdom |
| Germany | Indonesia | Ireland |
| Finland | Norway | France |
| Thailand | Latvia | |

This table presents the sample of sovereigns which have the largest percent of their population vulnerable to extreme sea level rise hazard according to results of various climate studies. The 14 sovereigns selected in each panel have the greatest percent of their population exposed to *ESL* hazard amongst the full sample of 59 sovereigns after accounting for preexisting protection standards (Lincke and Hinkel, 2018). In each panel, the sovereigns are listed from left to right according to their percent of exposure. In Panel A, exposure to *ESL* hazard is calculated by averaging the yearly percent of a sovereign population vulnerable to 1-in-100 year coastal floods based on data from Vafeidis et al. (2011) and Neumann et al. (2015). In panel b, estimates of exposure are from NASA's Shuttle Radar Topography Mission used to map global coastal elevation. Panel C uses estimates of elevation from the ALOS Global Digital Surface Model from the Japan Aerospace Exploration Agency (JAXA). Data for percent of population exposed under these two methodologies are obtained from Kulp and Strauss (2019).

Table 8: Marginal effects of news on sovereign CDS returns conditional on exposure to extreme sea level hazard, according to various data sources

| | SRTM (a) | | | JAXA (b) | | |
|---|---|---|---|---|---|---|
| | (1) 1 Yr | (2) 5 Yr | (3) 10 Yr | (4) 1 Yr | (5) 5 Yr | (6) 10 Yr |
| More Exposed × International Summits | 3.603 | 2.855* | 3.533** | 4.373 | 4.672*** | 4.896*** |
| | (3.077) | (1.640) | (1.340) | (3.147) | (1.614) | (1.399) |
| Less Exposed × International Summits | 2.910 | 1.291 | 1.496 | 2.140 | 0.939 | 0.903 |
| | (1.767) | (1.024) | (0.928) | (1.785) | (0.940) | (0.905) |
| SPX Returns | -1.741*** | -0.919*** | -0.730*** | -1.571*** | -0.809*** | -0.654*** |
| | (0.179) | (0.078) | (0.061) | (0.187) | (0.075) | (0.064) |
| MSCI Local Returns | -1.151*** | -0.505*** | -0.378*** | -1.104*** | -0.488*** | -0.363*** |
| | (0.160) | (0.065) | (0.050) | (0.160) | (0.065) | (0.051) |
| Debt to GDP | -0.105 | -0.032 | -0.044 | -0.012 | 0.012 | -0.005 |
| | (0.118) | (0.081) | (0.056) | (0.150) | (0.099) | (0.070) |
| MSCI Vol | 0.029*** | 0.014*** | 0.011*** | 0.027*** | 0.015*** | 0.011*** |
| | (0.007) | (0.004) | (0.003) | (0.008) | (0.003) | (0.002) |
| FTSE Bond Index | -1.141*** | -0.380*** | -0.318*** | -0.837*** | -0.311*** | -0.258*** |
| | (0.328) | (0.115) | (0.096) | (0.310) | (0.112) | (0.093) |
| Exchange Rate Dollar | 0.203 | 0.333* | 0.213 | 0.469** | 0.486*** | 0.344*** |
| | (0.255) | (0.173) | (0.129) | (0.195) | (0.085) | (0.060) |
| Intl Reserves | -0.000*** | 0.000*** | 0.000*** | -0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 5 Yr Treasury | 0.082** | 0.019 | -0.001 | 0.093** | 0.015 | -0.005 |
| | (0.037) | (0.012) | (0.010) | (0.037) | (0.011) | (0.009) |
| VIX | -0.031 | -0.013 | -0.014** | -0.033 | -0.011 | -0.013** |
| | (0.025) | (0.009) | (0.006) | (0.025) | (0.009) | (0.006) |
| SovereignxMonth | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R Squared | 0.310 | 0.377 | 0.351 | 0.293 | 0.365 | 0.335 |
| Observations | 5075 | 5086 | 5092 | 5081 | 5083 | 5089 |

This table presents regression results linking climate change news during international climate summits with 1-, 5-, and 10-year sovereign CDS returns for countries at risk from extreme sea level (ESL) hazards according to various elevation models. The coefficients in the first two rows show the marginal effects of the news index on returns, conditional on sovereigns being more or less exposed to the hazard. The "more exposed" sample of sovereigns in panel (a)—14 in total denoted in panel (b) of Table 7—consists of the more exposed sovereigns according to elevation data from NASA's Shuttle Radar Topography Mission. The "more exposed" group of sovereigns in panel (b) are according to elevation data from the Japan Aerospace Exploration Agency (JAXA). The coefficients in the first two rows represent the marginal effects of $InternationalSummits$ on returns based on exposure. Data for ESL hazard exposure under these two methodologies is obtained from Kulp and Strauss (2019). The $InternationalSummits$ index from Faccini et al. (2023) measures media attention to climate summits. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. All models include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The table reports regression coefficients of sovereign CDS returns, multiplied by 100, for the 1-, 5-, and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

Table 9: Differential effect of news on sovereign CDS returns by exposure to changes in extreme sea level hazard under other scenarios

| | Scenario A | | Scenario B | | Scenario C | | Scenario D | |
|---|---|---|---|---|---|---|---|---|
| | (1) 5 Yr | (2) 10 Yr | (3) 5 Yr | (4) 10 Yr | (5) 5 Yr | (6) 10 Yr | (7) 5 Yr | (8) 10 Yr |
| Exposed × Intl Summits | -2.258 | -1.888 | -2.703 | -2.486 | -3.291 | -3.198 | -3.291 | -3.198 |
| | (2.652) | (2.205) | (2.587) | (2.149) | (2.542) | (2.090) | (2.542) | (2.090) |
| Intl Summits | 3.995* | 4.142** | 4.208* | 4.428** | 4.491** | 4.766** | 4.491** | 4.766** |
| | (2.094) | (1.840) | (2.030) | (1.759) | (2.079) | (1.825) | (2.079) | (1.825) |
| SPX Returns | -0.895*** | -0.742*** | -0.894*** | -0.742*** | -0.893*** | -0.741*** | -0.893*** | -0.741*** |
| | (0.105) | (0.074) | (0.104) | (0.074) | (0.104) | (0.074) | (0.104) | (0.074) |
| MSCI Local Returns | -0.684*** | -0.491*** | -0.685*** | -0.492*** | -0.685*** | -0.492*** | -0.685*** | -0.492*** |
| | (0.090) | (0.065) | (0.090) | (0.065) | (0.090) | (0.065) | (0.090) | (0.065) |
| Debt to GDP | 0.027 | -0.070 | 0.029 | -0.069 | 0.028 | -0.070 | 0.028 | -0.070 |
| | (0.417) | (0.367) | (0.416) | (0.365) | (0.414) | (0.363) | (0.414) | (0.363) |
| MSCI Vol | 0.021*** | 0.011** | 0.021*** | 0.011** | 0.021*** | 0.011** | 0.021*** | 0.011** |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| FTSE Bond Index | -0.113 | -0.038 | -0.112 | -0.037 | -0.111 | -0.037 | -0.111 | -0.037 |
| | (0.211) | (0.170) | (0.211) | (0.170) | (0.211) | (0.170) | (0.211) | (0.170) |
| Exchange Rate Dollar | 0.056 | 0.027 | 0.057 | 0.027 | 0.056 | 0.027 | 0.056 | 0.027 |
| | (0.199) | (0.136) | (0.200) | (0.137) | (0.201) | (0.138) | (0.201) | (0.138) |
| Intl Reserves | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 5 Yr Treasury | 0.025 | 0.001 | 0.025 | 0.001 | 0.025 | 0.001 | 0.025 | 0.001 |
| | (0.018) | (0.015) | (0.018) | (0.015) | (0.018) | (0.015) | (0.018) | (0.015) |
| VIX | -0.015 | -0.020** | -0.015 | -0.020** | -0.015 | -0.020** | -0.015 | -0.020** |
| | (0.013) | (0.008) | (0.013) | (0.008) | (0.013) | (0.008) | (0.013) | (0.008) |
| SovereignxMonth | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R Squared | 0.284 | 0.249 | 0.284 | 0.250 | 0.284 | 0.250 | 0.284 | 0.250 |
| Observations | 2660 | 2660 | 2660 | 2660 | 2660 | 2660 | 2660 | 2660 |

This table shows coefficients from a model linking news on international climate summits to 5- and 10-year sovereign CDS returns for countries vulnerable to changes in extreme sea level hazard. The $InternationalSummits$ index from Faccini et al. (2023) measures media attention to climate summits and is interacted with $Exposed$ to produce the first-row coefficients, indicating the differential impact on CDS spreads between exposure groups. To calculate $\Delta ESL$, I begin with the 23 most exposed sovereigns to coastal flooding (fourth and fifth quintiles, Table 4). For each panel a-c, the changes in $ESL$ hazard are approximated by the coefficient obtained from regressing the forecasted percent of population exposed to 1-in-100 year coastal floods on a linear time trend. Each panel corresponds to population forecasts obtained from Vafeidis et al. (2011) under climate and population growth scenarios A through C developed by the UK Government's Foresight project. Sovereigns are split into more exposed (1) and less exposed (0) groups, represented by $Exposed$, based on whether a sovereign's trend coefficient is above or below the median across the 23 sovereigns. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. All models include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The coefficients of sovereign CDS returns are multiplied by 100, for the 5- and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

Table 10: Marginal effects of news on sovereign CDS returns conditional on exposure to extreme sea level hazards, according to various data sources

| | (1)<br>1 Yr | (2)<br>5 Yr | (3)<br>10 Yr |
|---|---|---|---|
| More Exposed × International Summits | 6.864 | 2.712* | 3.247** |
| | (1.00) | (1.69) | (2.68) |
| Less Exposed × International Summits | -3.471 | -0.025 | 1.000 |
| | (-1.20) | (-0.03) | (1.52) |
| SPX Returns | -1.337*** | -0.829*** | -0.687*** |
| | (-4.08) | (-11.68) | (-11.45) |
| MSCI Local Returns | -1.295*** | -0.449*** | -0.349*** |
| | (-6.55) | (-7.44) | (-7.58) |
| Debt to GDP | 0.038 | -0.029 | -0.027 |
| | (0.16) | (-0.38) | (-0.46) |
| MSCI Vol | 0.026** | 0.010*** | 0.006** |
| | (2.33) | (3.05) | (2.40) |
| FTSE Bond Index | -1.924*** | -0.428*** | -0.377*** |
| | (-3.06) | (-3.77) | (-3.83) |
| Exchange Rate $ | -0.255 | 0.197 | 0.138 |
| | (-1.00) | (1.37) | (1.27) |
| Intl Reserves | -0.000*** | 0.000*** | 0.000*** |
| | (-32.42) | (53.14) | (19.54) |
| 5 Yr Treasury | 0.098 | 0.007 | -0.011 |
| | (1.37) | (0.53) | (-1.13) |
| VIX | 0.049 | -0.004 | -0.011 |
| | (1.26) | (-0.45) | (-1.67) |
| SovereignxMonth | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes |
| Adj R Squared | 0.118 | 0.284 | 0.260 |
| Observations | 5084 | 5084 | 5084 |

This table presents regression results linking climate change news related to international summits with sovereign CDS premium returns at 1-, 5-, and 10-year maturities for countries at risk from extreme sea level (ESL) hazard. Premiums are obtained by decomposing sovereign CDS spreads using the reduced-form model of Longstaff et al. (2011). The coefficients in the first two rows show the marginal effects of the news index on returns derived from premiums, conditional on sovereigns being more or less exposed to the hazard. "More Exposed" refers to the group of sovereigns in the fourth quartile of Table 4, and "Less Exposed" refers to those in the first and second quartiles. ESL hazard exposure is gathered from Vafeidis et al. (2011) by calculating percentage of a population at risk from 1-in-100 year coastal floods for the year 2000. The $InternationalSummits$ index from Faccini et al. (2023) measures media attention. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. All models include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The table reports regression coefficients of sovereign CDS premium returns, multiplied by 100, for the 1-, 5-, and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *

Table 11: Differential effect of news on sovereign CDS premiums by exposure to changes in extreme sea level hazard under other scenarios

| | Forecasted $\Delta ESL$ (a) | | Observed $\Delta ESL$(b) | |
|---|---|---|---|---|
| | (1) 5 Yr | (2) 10 Yr | (3) 5 Yr | (4) 10 Yr |
| Exposed × International Summits | -2.506 | -2.612 | -1.984 | -1.382 |
| | (2.680) | (2.001) | (2.591) | (1.990) |
| International Summits | 3.070 | 4.458*** | 2.809 | 3.871** |
| | (2.078) | (1.572) | (2.195) | (1.730) |
| Debt to GDP | 0.288 | 0.124 | 0.301 | 0.137 |
| | (0.481) | (0.390) | (0.488) | (0.398) |
| MSCI Vol | 0.020*** | 0.011** | 0.020*** | 0.011** |
| | (0.006) | (0.005) | (0.006) | (0.005) |
| FTSE Bond Index | -0.201 | -0.146 | -0.200 | -0.145 |
| | (0.205) | (0.177) | (0.205) | (0.177) |
| SPX Returns | -0.879*** | -0.727*** | -0.879*** | -0.727*** |
| | (0.089) | (0.067) | (0.090) | (0.067) |
| MSCI Local Returns | -0.625*** | -0.470*** | -0.625*** | -0.470*** |
| | (0.076) | (0.064) | (0.077) | (0.064) |
| Exchange Rate $ | 0.010 | -0.013 | 0.014 | -0.010 |
| | (0.189) | (0.138) | (0.188) | (0.136) |
| Intl Reserves | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 5 Yr Treasury | 0.039** | 0.010 | 0.039** | 0.010 |
| | (0.017) | (0.015) | (0.017) | (0.015) |
| VIX | -0.010 | -0.019* | -0.010 | -0.019* |
| | (0.015) | (0.009) | (0.015) | (0.009) |
| SovereignxMonth | Yes | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes | Yes |
| Adj R Squared | 0.283 | 0.250 | 0.283 | 0.250 |
| Observations | 2641 | 2647 | 2641 | 2647 |

This table shows coefficients from a model linking news on international climate summits to 5- and 10-year sovereign CDS premium returns for countries vulnerable to changes in extreme sea level hazard. Premiums are obtained by decomposing sovereign CDS spreads using the reduced-form model of Longstaff et al. (2011). The $InternationalSummits$ index from Faccini et al. (2023) measures media attention to climate summits and is interacted with *Exposed* to produce the first-row coefficients, indicating the differential impact on premium returns between exposure groups. To calculate $\Delta ESL$, I begin with the 23 most exposed sovereigns to coastal flooding (fourth and fifth quintiles, Table 4). For panel (a), $\Delta ESL$ is derived by regressing the forecasted percentage of the population exposed to 1-in-100 year coastal floods on a linear time trend. Population and SLR forecasts come from Vafeidis et al. (2011). For panel (b), $\Delta ESL$ is calculated similary but uses observed population exposure data (2000-2010). Sovereigns are split into more exposed (1) and less exposed (0) groups, represented by *Exposed*, based on whether a sovereign's trend coefficient is above or below the median across the 23 sovereigns. Splits are shown in Figures 2 and 3. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. All models include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The coefficients of sovereign CDS returns are multiplied by 100, for the 5- and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

Table 12: Sensitivity of sovereign CDS returns to news for sovereigns protected against extreme sea level hazard

| | (1)<br>1 Yr | (2)<br>5 Yr | (3)<br>10 Yr |
|---|---|---|---|
| International Summits | 0.545 | 1.310 | 0.164 |
| | (8.210) | (3.655) | (3.246) |
| SPX Returns | -1.596** | -0.558** | -0.508** |
| | (0.554) | (0.198) | (0.171) |
| MSCI Local Returns | -1.319** | -0.558** | -0.436** |
| | (0.403) | (0.206) | (0.162) |
| Debt to GDP | -0.176*** | -0.077* | -0.068 |
| | (0.039) | (0.034) | (0.034) |
| MSCI Vol | 0.032 | 0.010 | 0.005* |
| | (0.034) | (0.008) | (0.002) |
| FTSE Bond Index | -0.680 | -0.271 | -0.267 |
| | (0.850) | (0.276) | (0.253) |
| Exchange Rate Dollar | 0.043 | 0.512*** | 0.429*** |
| | (0.762) | (0.096) | (0.064) |
| Intl Reserves | -0.034 | -0.018 | -0.058*** |
| | (0.018) | (0.019) | (0.009) |
| 5 Yr Treasury | 0.033 | -0.030 | -0.049 |
| | (0.090) | (0.037) | (0.033) |
| VIX | -0.055 | -0.011 | -0.020 |
| | (0.086) | (0.021) | (0.011) |
| SovereignxMonth | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes |
| Adj R Squared | 0.173 | 0.204 | 0.170 |
| Observations | 686 | 693 | 693 |

This table reports the regressions that relates climate change news surrounding international summits to 1-, 5-, and 10-year sovereign CDS returns for sovereigns protected against 1-in-100 year coastal floods. The sample of sovereigns that are protected, based on Lincke and Hinkel (2018), include Hong Kong, Israel, Italy, Qatar, Bahrain, and the Netherlands. The regressions are estimated with country by month and credit rating fixed effects for the sample period January 2010 to November 2019. $International summits$ is a time-series index developed in **?** that captures global media attention to international climate summits across Reuters newswires. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. All models include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The table reports regression coefficients of sovereign CDS returns, multiplied by 100, for the 1-, 5-, and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

Table 13: Sensitivity of sovereign CDS premium to news for sovereigns protected against extreme sea level hazard

| | (1)<br>1 Yr | (2)<br>5 Yr | (3)<br>10 Yr |
|---|---|---|---|
| International Summits | -10.645 | -0.913 | -0.233 |
| | (-0.89) | (-0.61) | (-0.29) |
| SPX Returns | -1.243 | -0.642** | -0.551** |
| | (-1.22) | (-2.96) | (-2.99) |
| MSCI Local Returns | -1.459* | -0.393 | -0.301 |
| | (-2.54) | (-1.86) | (-1.79) |
| Debt to GDP | -0.181** | -0.102** | -0.079*** |
| | (-2.84) | (-3.84) | (-4.11) |
| MSCI Vol | 0.010 | 0.008 | 0.002 |
| | (0.20) | (1.00) | (0.63) |
| FTSE Bond Index | -1.098 | -0.605* | -0.562*** |
| | (-0.79) | (-2.44) | (-4.13) |
| Exchange Rate $ | 0.484 | 0.222** | 0.229*** |
| | (0.47) | (2.66) | (7.34) |
| Intl Reserves | 0.116* | -0.023 | -0.034* |
| | (2.18) | (-1.09) | (-2.10) |
| 5 Yr Treasury | -0.099 | -0.060 | -0.065** |
| | (-0.83) | (-1.73) | (-2.72) |
| VIX | 0.034 | -0.007 | -0.010 |
| | (0.39) | (-0.59) | (-0.72) |
| SovereignxMonth | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes |
| Adj R Squared | 0.077 | 0.208 | 0.207 |
| Observations | 691 | 699 | 695 |

This table reports the regressions that relates climate change news surrounding international summits to 1-, 5-, and 10-year sovereign CDS premium returns. Premiums are obtained by decomposing sovereign CDS spreads using the reduced-form model of Longstaff et al. (2011). The sample of sovereigns that are protected, based on Lincke and Hinkel (2018), include Hong Kong, Israel, Italy, Qatar, Bahrain, and the Netherlands. The regressions are estimated with country by month and credit rating fixed effects for the sample period January 2010 to November 2019. $International summits$ is a time-series index developed in **?** that captures global media attention to international climate summits across Reuters newswires. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. All models include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The table reports regression coefficients of sovereign CDS returns, multiplied by 100, for the 1-, 5-, and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

Table 14: Marginal effects of news on sovereign CDS net notional amounts conditional on exposure to extreme sea level hazard

| | (1) | (2) |
|---|---|---|
| Less Exposed × International Summits | 2.053* | 1.802 |
| | (1.027) | (1.111) |
| More Exposed × International Summits | 4.043** | 3.814** |
| | (1.490) | (1.505) |
| SPX Returns | | 0.108** |
| | | (0.046) |
| MSCI Local Returns | | 0.005 |
| | | (0.033) |
| Debt to GDP | | 0.172 |
| | | (0.162) |
| Exchange Rate Dollar | | -0.076 |
| | | (0.080) |
| Intl Reserves | | -0.000*** |
| | | (0.000) |
| 5 Yr Treasury | | 0.004 |
| | | (0.016) |
| VIX | | 0.013** |
| | | (0.005) |
| MSCI Vol | | 0.003 |
| | | (0.004) |
| FTSE Bond Index | | 0.353*** |
| | | (0.082) |
| Controls | No | Yes |
| SovereignxMonth | Yes | Yes |
| Rating | Yes | Yes |
| Adj R Squared | 0.016 | 0.021 |
| Observations | 2662 | 2662 |

This table reports the regressions that relates climate change news surrounding international summits to the log growth of net notional amounts aggregated across all sovereign CDS tenors. Weekly net notional amounts,a measure of credit risk transference, are obtained from the Depository Trust & Clearing Corporation and are averaged to the monthly frequency to match control variables. The coefficients in the first two rows show the marginal effects of the news index on the growth of net notional amounts, conditional on sovereigns being more or less exposed to the hazard. "More Exposed" refers to the group of sovereigns in the fourth quartile of Table 4, and "Less Exposed" refers to those in the first and second quartiles. ESL hazard exposure is gathered from Vafeidis et al. (2011) by calculating percentage of a population at risk from 1-in-100 year coastal floods for the year 2000. The $InternationalSummits$ index from Faccini et al. (2023) measures media attention to climate summits. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. All models include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The table reports regression coefficients of sovereign CDS returns, multiplied by 100, for the 1-, 5-, and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

Table 15: Marginal effects of news on sovereign CDS returns conditional on exposure to extreme sea level hazard, controlling for liquidity

| | (1) 1 Yr | (2) 5 Yr | (3) 10 Yr |
|---|---|---|---|
| Gamma | 3.008** | 0.041 | 0.449 |
| | (1.420) | (0.565) | (0.439) |
| More Exposed × International Summits | 2.954 | 3.830** | 4.329*** |
| | (3.010) | (1.732) | (1.368) |
| Less Exposed × International Summits | 1.413 | 0.401 | 0.348 |
| | (1.759) | (0.943) | (0.848) |
| SPX Returns | -1.593*** | -0.840*** | -0.676*** |
| | (0.186) | (0.075) | (0.063) |
| MSCI Local Returns | -1.125*** | -0.518*** | -0.381*** |
| | (0.150) | (0.065) | (0.049) |
| Debt to GDP | -0.034 | 0.022 | 0.009 |
| | (0.136) | (0.105) | (0.075) |
| MSCI Vol | 0.024*** | 0.012*** | 0.009*** |
| | (0.009) | (0.004) | (0.003) |
| FTSE Bond Index | -1.048*** | -0.458*** | -0.392*** |
| | (0.322) | (0.115) | (0.100) |
| Exchange Rate Dollar | 0.300 | 0.330** | 0.212* |
| | (0.265) | (0.160) | (0.119) |
| Intl Reserves | -0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) |
| 5 Yr Treasury | 0.093** | 0.015 | -0.006 |
| | (0.037) | (0.012) | (0.010) |
| VIX | -0.023 | -0.009 | -0.011* |
| | (0.024) | (0.008) | (0.006) |
| SovereignxMonth | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes |
| Adj R Squared | 0.308 | 0.381 | 0.355 |
| Observations | 5088 | 5094 | 5086 |

This table presents regression results linking climate change news related to international summits with sovereign CDS returns at 1-, 5-, and 10-year maturities for countries vulnerable to extreme sea level (ESL) hazards. The regressions include an additional variable, Gamma reported in the first row, which are the monthly price reversals for each tenor using the methodology in Bao et al. (2011). The second two rows report the coefficients from interacting the news attention index, *InternationalSummits*, with an indicator variable distinguishing countries more or less exposed to ESL hazard. "More Exposed" refers to the group of sovereigns in the fourth quartile of Table 4, and "Less Exposed" refers to those in the first and second quartiles. ESL hazard exposure is gathered from Vafeidis et al. (2011) by calculating percentage of a population at risk from 1-in-100 year coastal floods for the year 2000. The time-series news index is sourced from Faccini et al. (2023) and captures global media attention to international climate summits as reported on Reuters newswires. All regressions are estimated with country by month and credit rating fixed effects for the sample period January 2010 to November 2019. The table reports the regression coefficients of sovereign CDS returns, multiplied by 100, for the 1-, 5-, and 10-year maturities. Standard errors, reported in parentheses, are clustered by sovereign. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, *.

Table 16: Marginal effects of Google Trends on sovereign CDS returns conditional on exposure to extreme sea level hazard

| | (1) 1 Yr | (2) 5 Yr | (3) 10 Yr |
|---|---|---|---|
| More Exposed × Google Trends | 5.225 | 2.392** | 1.788** |
| | (3.908) | (0.756) | (0.594) |
| Less Exposed × Google Trends | -1.254 | 0.297 | 0.110 |
| | (1.940) | (0.638) | (0.515) |
| More Exposed | -0.334 | -0.378 | -0.140 |
| | (0.575) | (0.392) | (0.350) |
| MSCI Local Returns | -0.783*** | -0.362*** | -0.259*** |
| | (0.129) | (0.062) | (0.048) |
| Debt to GDP | -0.014 | 0.019 | 0.025 |
| | (0.105) | (0.101) | (0.069) |
| MSCI Vol | 0.014 | 0.006** | 0.006*** |
| | (0.009) | (0.002) | (0.002) |
| Exchange Rate Dollar | 0.431 | 0.328 | 0.237 |
| | (0.403) | (0.182) | (0.140) |
| Intl Reserves | -0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) |
| YearxMonth | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes |
| Adj R Squared | 0.360 | 0.466 | 0.448 |
| Observations | 4972 | 4978 | 4970 |

This table presents regression results linking climate change attention related to international summits with sovereign CDS returns at 1-, 5-, and 10-year maturities for countries vulnerable to extreme sea level (ESL) hazards. The coefficients in the first two rows represent the marginal effects of *Google Trends* on returns conditional on exposure. *Google Trends* is an indicator variable equal to 1 when the value of attention to the topic "United Nations Climate Change Conference" in a country, is greater than the 90th percentile and 0 otherwise. 'More Exposed" refers to the group of sovereigns in the fourth quartile of Table 4, and "Less Exposed" refers to those in the first and second quartiles. ESL hazard exposure is gathered from Vafeidis et al. (2011) by calculating percentage of a population at risk from 1-in-100 year coastal floods for the year 2000. The regressions control for the country specific covariates: the changes in exchange rate of the local currency to USD, changes in foreign currency reserves denominated in USD, local MSCI excess stock returns and their monthly volatility, and changes in debt-to-GDP ratio interpolated from a yearly frequency to monthly. All regressions are estimated with year by month and credit rating fixed effects for the sample period January 2010 to November 2019. The table reports the regression coefficients of sovereign CDS returns, multiplied by 100, for the 1-, 5-, and 10-year maturities. Standard errors, reported in parentheses, are clustered by sovereign and year. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, *.

Table 17: Panel vector autoregressions testing for sovereign CDS return predictability

| | Forecasted $\Delta ESL$ (a) | | Observed $\Delta ESL$ (b) | |
|---|---|---|---|---|
| | (1) Less Exposed | (2) More Exposed | (3) Less Exposed | (4) More Exposed |
| L.International Summits | 5.051** | 3.049* | 6.754*** | 0.354 |
| | (2.434) | (1.748) | (3.132) | (0.299) |
| L2.International Summits | 3.256** | 5.519** | 4.192*** | 3.931* |
| | (2.021) | (2.507) | (2.692) | (1.663) |
| L.10 Yr CDS Growth | -0.003 | 0.007 | 0.038 | -0.040 |
| | (-0.065) | (0.345) | (1.325) | (-1.235) |
| L2.10 Yr CDS Growth | -0.042* | 0.004 | 0.008 | -0.047** |
| | (-1.695) | (0.297) | (0.570) | (-1.979) |
| SPX Returns | -0.562*** | -0.852*** | -0.773*** | -0.689*** |
| | (-3.997) | (-5.715) | (-4.753) | (-5.060) |
| MSCI Local Returns | -0.526*** | -0.592*** | -0.502*** | -0.608*** |
| | (-4.685) | (-5.476) | (-4.366) | (-6.534) |
| Debt to GDP | 1.801* | 1.242* | 0.499 | 2.948*** |
| | (1.741) | (1.814) | (0.766) | (4.668) |
| MSCI Vol | 0.020*** | 0.015*** | 0.014*** | 0.021*** |
| | (3.885) | (3.159) | (3.162) | (3.553) |
| FTSE Bond Index | -0.021 | -0.294* | -0.177 | -0.164 |
| | (-0.133) | (-1.913) | (-1.217) | (-0.946) |
| Exchange Rate Dollar | 0.292* | -0.189 | -0.062 | 0.161 |
| | (1.871) | (-1.502) | (-0.398) | (1.237) |
| Intl Reserves | 0.000*** | 0.020 | 0.000*** | 0.048** |
| | (8.898) | (1.120) | (13.304) | (2.220) |
| 5 Yr Treasury | -0.018 | 0.021* | -0.014 | 0.013 |
| | (-0.730) | (1.717) | (-0.702) | (0.626) |
| VIX | -0.010 | -0.019* | -0.020** | -0.012 |
| | (-1.210) | (-1.732) | (-2.045) | (-1.407) |
| N | 1392 | 1276 | 1392 | 1276 |
| J | 5.475 | 9.426 | 4.363 | 3.538 |

This table reports the second order panel vector autoregressions are estimated to investigate the relationship between the two month lagged values of the climate summit news index and monthly sovereign CDS returns for trend coastal flooding exposed sovereigns. Each panel reports the regression coefficients of sovereign CDS returns, multiplied by 100, for 10-year maturities. The countries in panels (a) and (b) consist of the of the 23 sovereigns more exposed to *ESL* hazard, described in Table 4. For panel (a), the changes in *ESL* hazard are approximated by the coefficient obtained from regressing the forecasted (from Vafeidis et al. (2011)) percent of population exposed to 1-in-100 year coastal floods on a linear time trend. For panel (b), the changes in *ESL* hazard are approximated by the coefficient obtained from regressing the historical (2000 to 2010) percent of population exposed to floods on a linear time trend. For each panel, the sovereigns are split into less and more exposed groups by dividing the estimated coefficients by their median value. Splits are shown in Figures 2 and 3. The $InternationalSummits$ index from Faccini et al. (2023) measures media attention to climate summits and is interacted with *Exposed* to produce the first-row coefficients, indicating the differential impact on CDS spreads between exposure groups. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. All models include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The coefficients of sovereign CDS returns are multiplied by 100, for the 5- and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

Table 18: Marginal effects of news on sovereign CDS returns conditional on exposure to extreme sea level hazard, controlling for other climate risks

| | (1)<br>1 Yr | (2)<br>5 Yr | (3)<br>10 Yr |
|---|---|---|---|
| More Exposed × International Summits | 2.997 | 3.118* | 3.835*** |
| | (3.059) | (1.641) | (1.283) |
| Less Exposed × International Summits | 0.872 | -0.290 | -0.160 |
| | (1.780) | (0.982) | (0.868) |
| NDGAIN Exposure | -13.781 | -31.334* | -34.820** |
| | (37.249) | (17.056) | (16.322) |
| NDGAIN Infrastructure | -29.981 | -13.325 | -11.620 |
| | (22.301) | (11.367) | (10.903) |
| NDGAIN Readiness | -17.222 | -16.538** | -9.375 |
| | (10.676) | (7.323) | (5.969) |
| Other Controls | Yes | Yes | Yes |
| SovereignxMonth | Yes | Yes | Yes |
| Rating | Yes | Yes | Yes |
| Adj R Squared | 0.307 | 0.384 | 0.358 |
| Observations | 4972 | 4979 | 4971 |

This table presents regression results linking climate change news related to international summits with sovereign CDS returns at 1-, 5-, and 10-year maturities for countries at risk from extreme sea level (ESL) hazards. I control for metrics from the Notre Dame-Global Adaptation Index (ND-Gain). *Exposure* captures how climate change impacts human living conditions. *Infrastructure* is a metric of how coastal infrastructure will be impacted by the combined effect of sea level rise and potential storm surge. *Infrastructure* is a metric of how coastal infrastructure will be impacted by the combined effect of sea level rise and potential storm surge. *Readiness* measures a country's readiness to leverage private and public sector investment for adaptive actions. The coefficients in the first two rows represent the marginal effects of $InternationalSummits$ on returns based on exposure. "More Exposed" refers to the group of sovereigns in the fourth quartile of Table 4, and "Less Exposed" refers to those in the first and second quartiles. ESL hazard exposure is gathered from Vafeidis et al. (2011) by calculating percentage of a population at risk from 1-in-100 year coastal floods for the year 2000. I control for global covariates: changes in the 5-year Treasury yield, CBOE VIX, FTSE World Bond Index returns, and S&P 500 excess returns. Country-specific covariates include changes in the local currency to USD exchange rate, foreign currency reserves in USD, local MSCI excess stock returns and their volatility, and changes in the debt-to-GDP ratio interpolated from yearly to monthly. All models include country-by-month and credit rating fixed effects for the period January 2010 to November 2019. The table reports regression coefficients of sovereign CDS returns, multiplied by 100, for the 1-, 5-, and 10-year maturities. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

# 7 Figures

Figure 1: International Climate Summit News Index

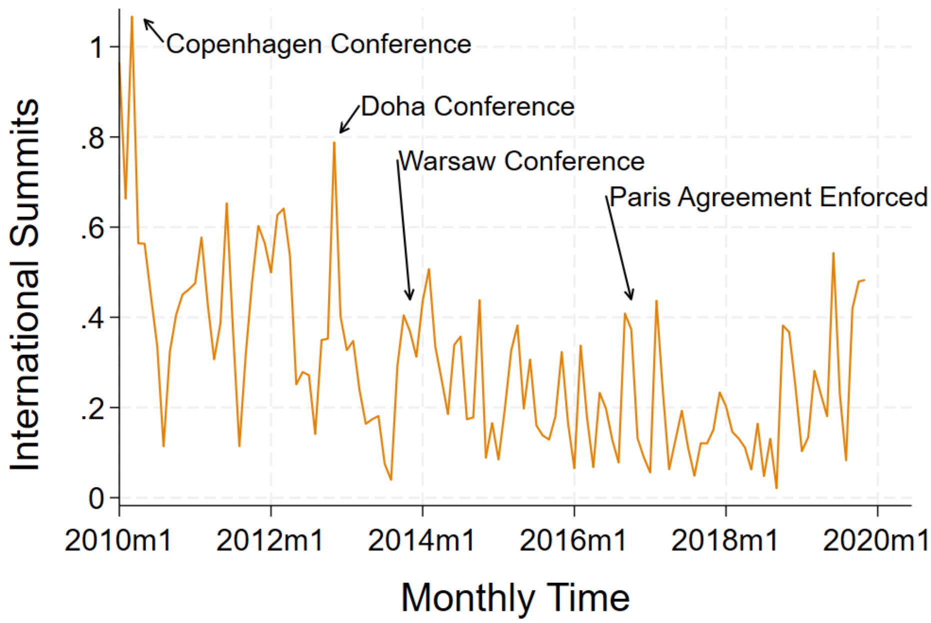



Figure 1 presents a time-series of the climate summits index obtained from Faccini et al. (2023). The index is developed using Reuters newswires as a corpus and then performing Latent Dirichlet Allocation to extract topics. The series is used as a proxy for attention to climate summits by the sovereign credit market.

Figure 2: Changes in extreme sea level hazard using forecasted data

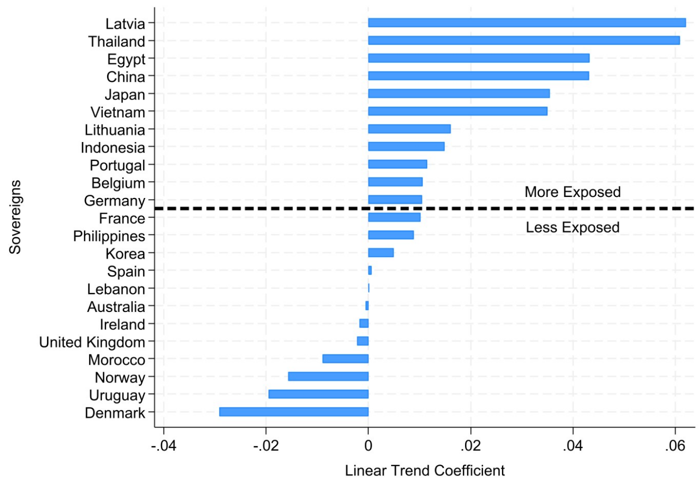



Figure 2 presents the change in exposure of sovereigns to extreme sea level rise hazard. The sample of sovereigns in the figure consist of the of the 23 sovereigns more exposed to *ESL* hazard, i.e., the fourth and fifth quintiles of vulnerable sovereigns as described in Table 4. The changes in *ESL* hazard are approximated by the coefficient obtained from regressing the forecasted percent of population exposed to 1-in-100 year coastal floods on a linear time trend. The forecasts are obtained from Vafeidis et al. (2011) and are equally weighted across scenarios A, B, C, and D. The sovereigns are split into less and more exposed groups by dividing the estimated coefficients by their median value.

Figure 3: Changes in extreme sea level hazard using observed data

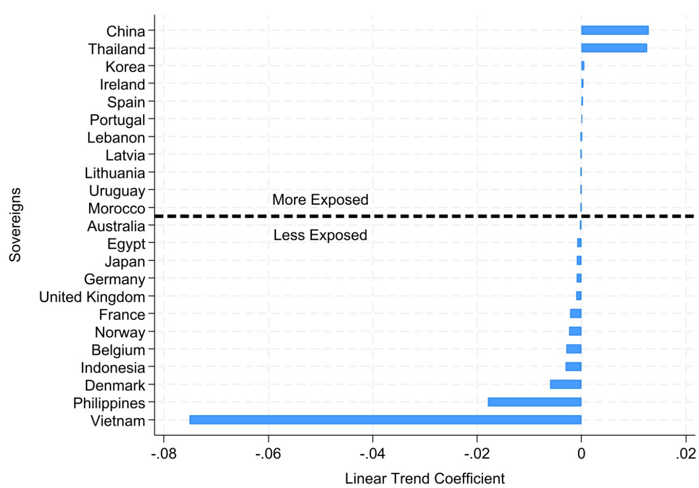



Figure 3 presents the change in exposure of sovereigns to extreme sea level rise hazard. The sample of sovereigns in the figure consist of the of the 23 sovereigns more exposed to *ESL* hazard, i.e., the fourth and fifth quintiles of vulnerable sovereigns as described in Table 4. The the changes in *ESL* hazard are approximated by the coefficient obtained from regressing the observed (2000 to 2010) percent of population exposed to 1-in-100 year coastal floods on a linear time trend. The sovereigns are split into less and more exposed groups by dividing the estimated coefficients by their median value.

Figure 4: Population of Ho Chi Minh City: total (Left) and vulnerable to extreme sea level hazard (Right)

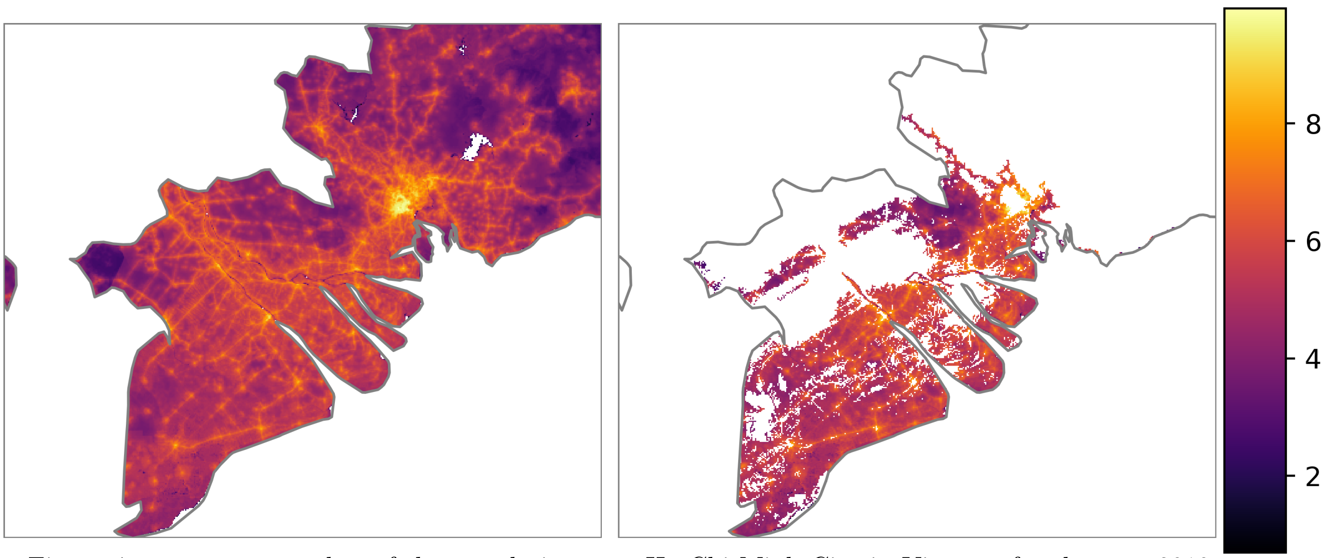
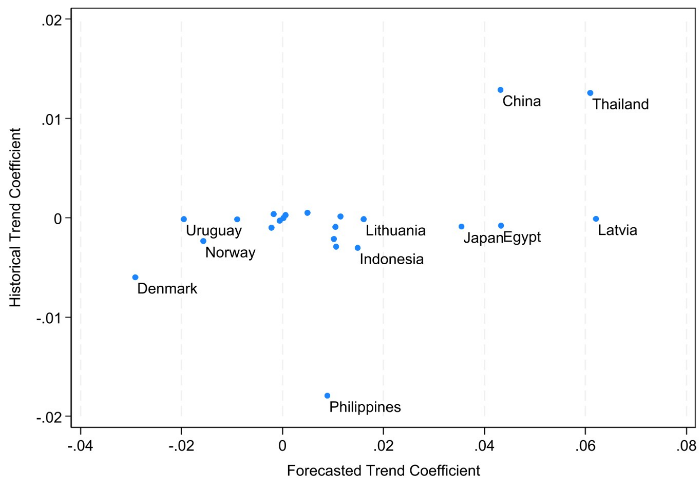



Figure 4 presents a snapshot of the population near Ho Chi Minh City in Vietnam for the year 2010. The left hand side presents the total population in log form obtained from the 2010 gridded dataset developed by WorldPop. The panel on the right illustrates the population exposed to extreme sea level (ESL) hazard. Exposure to *ESL* hazard is calculated by using the historical 1-in-100 year coastal flood exposure dataset developed by Muis et al. (2016). Then, I overlay the gridded population dataset and set any grid with greater than 30 centimeters of exposure to flooding as "exposed".

Figure 5: Comparison of estimated rates of change of exposure using observed and projected data




This figure presents a comparison between the linear trend coefficients estimated with observed versus projected data data. Vietnam is excluded because of readability. The sample of sovereigns in the figure consist of the of the 23 sovereigns more exposed to *ESL* hazard, i.e., the fourth and fifth quintiles of vulnerable sovereigns as described in Table 4. The values on the y-axis represent the changes in *ESL* hazard and are approximated by the coefficient obtained from regressing the historical (2000 to 2010) percent of population exposed to 1-in-100 year coastal floods on a linear time trend. The values on the y-axis similarly represent the change in *ESL* hazard, but use the forecasted percent of population exposed to 1-in-100 year coastal floods found in Vafeidis et al. (2011).

Figure 6: Cumulative abnormal returns for sovereigns vulnerable to extreme sea level hazard around the Paris Climate Summit

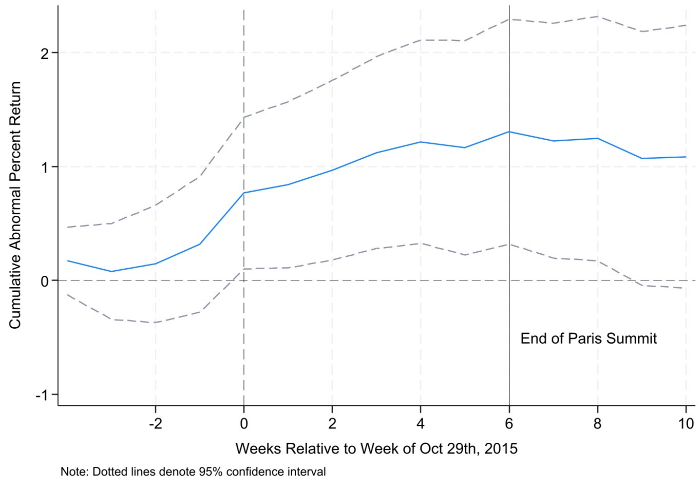



Figure 6 presents the cumulative abnormal returns (CAR) of the more exposed sovereigns to extreme sea level rise hazard around the last week of October 2015, the period immediately preceding the Paris Climate summit. The sample of sovereigns used to calculate CARs consist of the fourth quartile of extreme sea level (*ESL*) hazard exposed countries as described in Table 4. Exposure to *ESL* hazard is calculated by averaging the yearly percent of a sovereign population vulnerable to 1-in-100 year coastal floods between 2000 and 2010.

Figure 7: Cumulative abnormal returns for sovereigns not vulnerable to extreme sea level hazard around the Paris Climate Summit

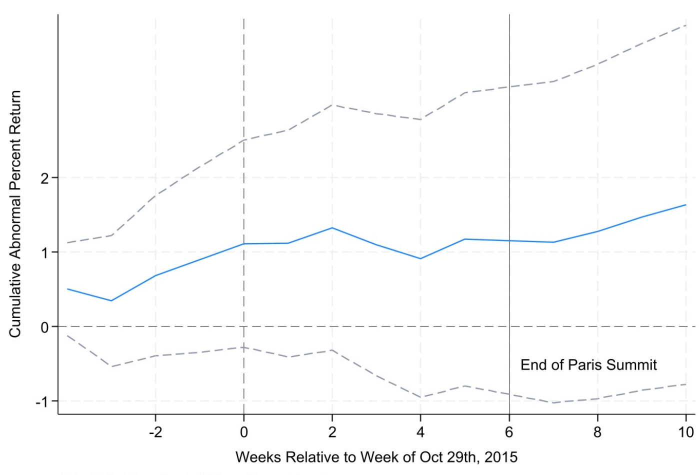



Figure 7 presents the cumulative abnormal returns of the less exposed sovereigns to extreme sea level rise hazard around the last week of October 2015, the period immediately preceding the Paris Climate summit. The sample of sovereigns used to calculate CARs consist of the first and second quartiles of extreme sea level (*ESL*) hazard exposed countries as described in Table 4. Exposure to *ESL* hazard is calculated by averaging the yearly percent of a sovereign population vulnerable to 1-in-100 year coastal floods between 2000 and 2019.

# 8 Appendix A

## 8.1 Sovereign CDS Net Notional Amounts

The evidence provided thus far implicitly tests for investor attention to SLR, as there would be no observed price reaction for sovereign CDS spreads if investors did not pay attention. The implied mechanism of increasing spreads is that the gross notional amounts and number of trades should rise during periods of high climate attention. In this case, counterparties (i.e., investors) react to climate summits by purchasing swaps to protect against potential default and credit risk premium rises for afflicted sovereigns, in turn increasing the equilibrium price of the sovereign CDS. In this case, I do not explicitly link investor behavior of purchasing more insurance with attention which I attempt to rectify in this robustness check.

To investigate sovereign CDS trading by investors, I follow the prior work of Oehmke and Zawadowski (2017) who study the determinants of CDS trading volumes, obtained from the Depository Trust and Clearing Corporation (DTCC).[21] The DTCC Section I data, previously available as open-source, contains weekly CDS position and trading data of single-name CDSs for the top 1,000 traded entities, including companies, sovereigns, and states. I obtain the weekly net notional amount outstanding from the DTCC between January 1, 2010 and March 25, 2016. I focus on the net notional outstanding as it represents the net protection bought by buyers or sellers across the market for an entity, and captures the aggregate credit risk exchanged in the market. Gross notional amounts, on the other hand, are a measure of the total transaction volume occurring in the market and could increase if a counterparty offsets an existing trade, thereby reducing the total credit risk transferred in the market.[22]

The net notional data provides a practical means for understanding whether there is elevated trading activity and risk transference during periods of elevated attention, further substantiating the increased spreads found in the main results. However, the DTCC data has considerable drawbacks, which relegates the analysis to a robustness check rather than a main result. The data represents activity across *all* tenors and is therefore more reliable for *ESL* analysis, as the hazard should affect medium to longer tenors. Additionally, the data is only available up to the first quarter of 2016 and measures the average weekly transactions for an entity, again diluting the measure. Finally, the DTCC only records the amounts if the CDS contract is in the top 1,000 traded that week across all entities (i.e., not only sovereigns). Some sovereigns, particularly in South America, with lower trading volumes do not appear

[21] The Warehouse is a trade repository which consolidates information such as trade reporting, payment calculation, credit event processing, and final settlement.

[22] The inaccuracies of gross notional amounts in measuring the total credit risk transferred in the CDS market has led the literature to predominantly focus on net notional amounts as the more economically relevant measure (see Oehmke and Zawadowski (2017)).

in the data, and others may drop out of the sample for a string of weeks. Therefore, I match the prior analysis and the frequency of the control variables, and aggregate the transactions to obtain the mean weekly net notional amount traded in a month.

Using the net notional data, I ask whether net notional amounts are associated with attention to the climate summit index for sovereigns vulnerable to coastal flooding hazard in order to verify $H_1$. I use the mean weekly net notional amounts in a month, and use their natural log changes as the dependent variable in a regression of the form:

$$\log\left(\frac{G_t}{G_{t-1}}\right) = \alpha + \beta_1(\mathit{Exposure}_i \times \mathit{Attention}_t) + \gamma \Delta X_{i,t} + \eta_i + \rho_{i,t_y} + \varepsilon_{i,t}, \qquad (12)$$

where $t$ denotes months and $G$ represents the net notional amounts. The sample is restricted to only include sovereigns that have more than 90% of their observations as non-missing and different from zero. This leaves the 14 original fourth-quartile sovereigns in the sample vulnerable to *ESL* hazard, and 23 from the bottom two quartiles remain in the unexposed group. The sovereigns that are not in the top thousand contracts traded, and therefore censored in the DTCC sample, are Uruguay, Dominican Republic, Costa Rica, Guatemala, Lebanon, Serbia, and El Salvador. I then project the net notional growth onto the attention index along with the same control variables and fixed effects as stated in equation 6.

The results of the regressions using net notional amounts as the dependent variable are shown in Table 14. Columns (1) and (2) indicate that the index is significantly (at 1%) related to increasing risk transfer activity for those sovereigns vulnerable to coastal flooding. In terms of economic magnitude, a one-unit increase in the index leads to about a 4% rise in net notional amounts. In comparison, there is a positive but non-significant relationship between the least exposed group and climate summit news. Although not precisely comparable, as these contracts are traded across all terms, the economic magnitude is similar to the relationship documented in Section 3.1.1, where I find a 0.80% rise in spreads. The evidence therefore supports hypothesis $H_1$ in that the counterparties participating in the CDS market perceive flood hazard as a material risk, and purchase net protection to hedge against it.

The evidence provided in this section points to the market purchasing sovereign default insurance during periods of attention to climate summits, paralleling the prior findings. Furthermore, it confirms that media attention is a significant factor in the growth of sovereign CDS trading volume—a novel contribution to the literature. This interpretation is in line with the findings of Augustin et al. (2016) who show that investors use sovereign CDS primarily as hedging instruments. The conclusions drawn from this investigation explicitly support the results showing that the cost of insurance rises to protect against countries that are most exposed during periods of global attention to climate hazards.

## 8.2 Liquidity

Generally, sovereign CDS are more liquid than a comparable sovereign bond with the same maturity (Mullin and Bruno, 2020). Moreover, relative to the corporate CDS market, trading in the sovereign market is less clustered around the 5-year contract and is distributed more evenly across tenors. Nonetheless, illiquidity may lead to investors demanding higher compensation for bearing the risk associated with the sovereign debt, leading to an increase in the CDS spread. Bao et al. (2011) capture liquidity using the negative of autocovariance of prices changes and show that the measure is a significant factor for pricing a cross-section of corporate bonds. Furthermore, they show that the variation explained by price reversals is substantially greater than what can be explained by bid-ask spreads. In this robustness check, I use the liquidity measure to show that prior results are not subsumed by potential illiquidity in the CDS market.

To obtain monthly price reversals, I collect daily CDS spreads, quoted at the end of the day, from Datastream for the 59 sovereigns in my sample from 2010 to the end of 2019. I define illiquidity, $\gamma$, with:

$$\gamma = -\operatorname{Cov}\left(\Delta p_t, \Delta p_{t+1}\right), \tag{13}$$

where $\Delta p_t = p_t - p_{t-1}$ is the price change from time $t-1$ to $t$. $\gamma$'s are calculated at a monthly frequency for each CDS tenor of all sovereigns in the sample. The time series of price reversals are used as an additional control variable in the empirical regressions in the form of specification 6.

Table 15 presents the results of the regressions including $\gamma$ as a control variable. The only significant estimate is located in the first column, indicating that the spreads of one-year CDS spreads are significantly explained by liquidity. These results are consistent with findings from Pan and Singleton (2008), who report that 1-year and 10-year contracts comprise approximately 10% and 20% of volumes in sovereign markets, respectively, with 5-year contracts showing the greatest liquidity. The statistical significance of $\gamma$ in the first column thus matches the fact that the lack of liquidity may be an issue for shorter maturities, leaving the underlying relationship between $ESL$ hazard and credit risk intact.

## 8.3 Alternative Attention Indices

As an additional robustness check, I further validate the empirical investigation by testing whether country level attention to international summits are reflected in sovereign CDS returns. Consistent with Hilscher and Nosbusch (2010), I view country level attention as a potential risk factor that can alarm investors towards *ESL* hazard.

Data gathered from country Google search volumes (SVI) on the topic "United Nations Climate Change Conference" are used to proxy for local investor attention, akin to Choi et al. (2020).[23] I collect the attention index for each sovereign from January 2004 to November 2019 and subset the data to only include information from January 2010 to November 2019.[24] SVI is a normalized index, presented on a scale from 0 to 100, where the volume of searches each month is scaled relative to the highest volume of searches in any given month within a specific time frame. However, this normalization process often results in numerous months where the index equals zero, leading to considerable sparsity within the index. In response, I assign an indicator variable, *Google Trends*, to 1 when above the index is above the 90th percentile and 0 otherwise. This results in a variable which represents particularly high periods of attention in a country towards international summits.

The estimation strategy relies on an interactive term between *Exposure* and *Google Trends* to understand the relationship between local attention and returns for each exposure group. For the 1, 5, and 10 year spreads ($R^{SCDS}_{i,t+1}$), I perform regressions of the following specification:

$$R^{SCDS}_{i,t+1} = \alpha + \beta_1(Exposure_i \times GTrends_{i,t}) + \beta_2(Exposure_i) + \gamma \Delta X_{i,t} + \lambda_t + \rho_{i,t_y} + \varepsilon_{i,t}, \quad (14)$$

for country, $i$, at time $t$. $\Delta X_{i,t}$ is a set of country specific variables to control for sovereign-specific factors that are known to affect sovereign CDS returns. I include $\lambda_i$ which represents year by month fixed effects to capture observable and observable heterogeneity between periods of time and subsume global covariates such as VIX. $\rho_{i,t_y}$ represents a fixed effect obtained by transforming a numerical credit-rating from Oxford Economics and mapping the series into five "risk buckets" that control for the yearly rating of each sovereign. The coefficient, $\beta_2$, captures the difference in the base levels of CDS returns between exposure groups, leaving the simple effects estimated from the interactive term.

The first two rows of Table 16 presents the estimated betas of the interactive term—the relationship between high levels of country-specific attention to international summits and CDS returns, conditional on exposure *ESL* hazard. The second row presents non-significant coefficients for the interactive terms, indicating no relationship between the CDS spreads and

[23]Specifically, I use the pytrends package in Python to collect historical time series information on the topic, m0rf7z0x.

[24]I opt to collect data from the inception of Google trends to include all available information up to November 2019. The only sovereign with missing information on the topic is Latvia which is excluded from the sample.

local attention for sovereigns with lesser exposure to extreme sea level rise. In contrast, the exposed countries (first row) present positive and significant coefficients, for 5 and 10 year CDS spreads. I note that the coefficient on the interactive term for more exposed sovereigns is large due to the greater volatility of shorter term spreads.

The results confirm a modest relationship between country level attention towards the topic "United Nations Climate Change Conference" and risk for vulnerable countries, supporting the prior results. My results lend credence to a combination of global and local factors that drive variation in sovereign risk, similar to the conclusions of Dieckmann and Plank (2012). Although these results are incomparable to prior specifications due to the inherent non-linearities of the indicator *Google Trends*, it is possible to draw some broad conclusions. The markedly smaller coefficient sizes suggest that while returns are sensitive to local attention, the effects are limited. This relationship suggests that global rather than local attention to international summits drives CDS returns for vulnerable sovereigns.

## 8.4 Panel Vector Autoregressions

I express a PVAR estimated using generalized method of moments, as:

$$\begin{bmatrix} \text{Attention}_{\,t} \\ R^{SCDS}_{i,t+1} \\ X_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \sum_{p=1}^{n} \begin{bmatrix} \beta_{1,p} & \beta_{2p} \\ \beta_{3,p} & \beta_{4,p} \\ \beta_{5,p} & \beta_{6,p} \end{bmatrix} \begin{bmatrix} \text{Attention}_{\,t-p} \\ R^{SCDS}_{i,t-p} \\ X_{i,t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix}, \tag{15}$$

for sovereign $i$ and $p$ lags. The attention index, $Attention_t$ and sovereign CDS returns, $R^{SCDS}_{i,t+1}$, are the endogenous vectors of interest, and $X_{i,t}$ is an exogenous vector of control variables used in regression 6. Before estimation, I verify with Dickey Fuller unit root tests and panel unit root tests that both global and sovereign-specific variables are stationary. I find that a second-order panel VAR model, estimated with the first three lags of the untransformed variables as instruments, is found to produce an insignificant $J$ statistic.[25] I apply this structural regression to the *ESL*- and $\Delta ESL$-exposed groups with a Helmert transformation to remove sovereign-specific fixed effects.

The results for the PVAR regression estimate for the $\Delta ESL$-exposed sovereigns are presented in Table 17, which illustrates that the sovereign CDS market is inattentive to news when pricing coastal flooding hazard. Specifically, the second lag of international summits has a statistically significant positive relationship with sovereign CDS returns across all subgroups of sovereigns. The lagged relationship is in support of hypothesis $H_2$ in that the market

[25]The GMM estimation is performed with the Stata module developed by Abrigo and Love (2016).

gradually incorporates longer-term risk, as in DellaVigna and Pollet (2007). There is also no observed return reversal across all specifications, implying that the investors value climate related news but are encumbered by challenges in information processing, leading to an underreaction in the market. Nonetheless, the relative similarity in magnitude and significance of the coefficient of interest across all specifications hinders cross-group comparisons.

In sum, the observed evidence supports a behavioral inattention story rather than one of rational inattention. Investors, faced with the added complexity of processing climate information, gradually integrate subsets of publicly available information. If investors are rationally inattentive, then magnitudes across the entire sample would likely be smaller, implying weak predictability (Sims (2003); Van Nieuwerburgh and Veldkamp (2010)).

### 8.5 Controlling for Other Risks

Other climate risks discussed during international summits could potentially affect the estimated relationship. To account for this, I utilize sovereign-specific indices developed by the Notre Dame Global Adaptation Initiative (ND-GAIN), which offers open-source metrics measuring a country's vulnerability to climate disruptions (Chen et al., 2015). Specifically, I incorporate three indices: human exposure to climate risks, national infrastructure vulnerability, and the readiness of a country to adapt to climate change. This section demonstrates that incorporating these additional indices does not alter the original relationship between international summits and sovereign CDS spreads.

Table 18 includes the three indicators: Exposure, Infrastructure, and Readiness. Exposure assesses a country's vulnerability to climate change by evaluating sensitivity to climate factors. Infrastructure quantifies a country's vulnerability and adaptive capacity regarding infrastructure in the face of climate change. Readiness measures a country's capability to efficiently utilize investments for climate adaptation. Again, the contemporaneous correlation between the news index and credit risk is significantly positive for medium to long term CDS tenors.

## 9 Appendix B

I outline the decomposition method, developed in Pan and Singleton (2008) and Longstaff et al. (2011), for the term structure of sovereign CDS spreads.

The risk-neutral default intensity at time t, $\lambda_t$, is described as the first jump of a Poisson process following the stochastic differential equation,

$$d \ln \lambda_t = \kappa^Q \left(\theta^Q - \ln \lambda_t\right) dt + \sigma_\lambda dB_t^Q, \tag{16}$$

where $\kappa$, $\theta$, and $\sigma$ account for the speed of mean-reversion, the long-run mean, and the volatility of the Ornstein-Uhlenbeck process. By modelling the intensity in this form, a *sovereign CDS* contract can be priced in its present value form at time $t$ and maturity $M$ as,

$$SCDS_t(M) = \frac{2\left(1 - R^Q\right) \int_t^{t+M} E_t^Q \left[\lambda_u e^{-\int_t^u (r_s + \lambda_s) ds}\right] du}{\sum_{j=1}^{2M} \left[E_t^Q e^{-\int_t^{t+j/2} (r_s+\lambda_s) ds}\right]} \tag{17}$$

where the numerator is the contingent payment paid by the protection seller upon a credit event, i.e., the premium leg. The denominator can be thought of as the protection leg, representing the discounted value of a semiannual annuity, contingent on a default event not occurring or maturity. $R^Q$ represents the constant risk-neutral fractional recovery, 25%, of face value on the underlying cheapest to deliver bond in the event of a relevant credit event. The variable $r_t$ denotes the riskless interest rate, while $\lambda_t$ represents the risk-neutral intensity or arrival rate of a credit event. The riskless rate and default intensity are assumed to follow a stochastic process and evolve independently, therefore implying that the term structure can be specified exogenously. This continuous-time model is then approximated and discretized to include the price of a default free bond, $D(t, u)$, that matures at time $u$,

$$SCDS_t^Q(M) = \frac{2\left(1 - R^Q\right) \int_t^{t+M} D(t,u) E_t^Q \left[\lambda e^{-\int_t^u \lambda_s ds}\right] du}{\sum_{j=1}^{2M} D(t, t+j/2) E_t^Q \left[e^{-\int_t^{t+j/2} \lambda_s ds}\right]}. \tag{18}$$

Thus far, the framework has defined pricing under risk-neutral conditions, however, there is an equivalent historical data generating process of form $\mathbb{P}$. Under this historical, objective measure, default intensity is described as,

$$d \ln \lambda_t = \kappa^P \left(\theta^P - \ln \lambda_t\right) dt + \sigma_\lambda dB_t^P, \tag{19}$$

and can be linked to the risk neutral intensity process, $\mathbb{Q}$, by the market price of risk,

$$\eta_t = \delta_0 + \delta_1 \ln \lambda_t. \tag{20}$$

The parameters that determine the price of risk, $\delta_0$ and $\delta_1$, satisfy $\kappa^Q = \kappa^P + \delta_1 \sigma_\lambda$ and $\kappa^Q \theta^Q = \kappa^P \theta^P - \delta_0 \sigma_\lambda$. If $\delta_0$ and $\delta_1$ are equal to zero there would be no difference between the risk-neutral and historical processes, implying no apparent risk premium in spreads. Otherwise, if there is a premium,

$$SCDS_t^P(M) = \frac{2\left(1 - R^Q\right)\int_t^{t+M} D(t,u)E_t^P\left[\lambda e^{-\int_t^u \lambda_s ds}\right]du}{\sum_{j=1}^{2M} D(t,t+j/2)E_t^P\left[e^{-\int_t^{t+j/2}\lambda_s ds}\right]} \tag{21}$$

would diverge from $SCDS_t^Q(M)$. Specifically, to obtain the default "distress" risk premium, $SCDS_t^P(M)$ is subtracted from $SCDS_t^Q(M)$.

Estimation of the premium is obtained using the 1-, 5-, and 10-year sovereign CDS spreads and Maximum-Likelihood as there is no closed-form solution. I assume the theoretical 1-year and 10-year sovereign CDS contracts as priced with normally distributed errors of mean zero and standard deviations $\sigma_\epsilon(1)$ and $\sigma_\epsilon(10)$. I choose the 5-year sovereign CDS as perfectly priced conditional on a set of parameters $\kappa^Q, \theta^Q$ and $\sigma$ to recover $\lambda$ using the inverse of the pricing function. Values of the zero-coupon bonds that are apparent in the discrete pricing formula are from the Treasury constant maturity curve published by the Federal Reserve Board and interpolated using cubic spline interpolation. Lastly, the joint density function is,

$$\begin{aligned} f^P(\Theta,\lambda) =& f^P\left(\epsilon_{1y} \mid \sigma_\epsilon(1)\right) \times f^P\left(\epsilon_{10y} \mid \sigma_\epsilon(10)\right) \times f^P\left(\ln\lambda \mid \kappa^P, \kappa^P\theta^P, \sigma\right) \\ & \times \left|\partial SCDS^Q\left(\lambda \mid \kappa^Q, \kappa^Q\theta^Q, \sigma\right)/\partial\lambda\right|^{-1}, \end{aligned} \tag{22}$$

where the parameter vector is $\Theta = \left(\kappa^Q, \kappa^Q\theta^Q, \kappa^P, \sigma_\lambda, \sigma_\varepsilon(1), \sigma_\varepsilon(10)\right)$ with $\Delta t$ being equal to 1/12 due to the monthly frequency of the data.