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

This study examines whether the sovereign credit market incorporates expectations of coastal flooding and sea level rise (SLR). The results indicate that medium- and long-term credit default swap spreads increase for sovereigns with a substantial portion of their population vulnerable to ex-ante coastal flooding in response to news around climate summits. Predictability tests suggest that the market asynchronously incorporates changing vulnerabilities of regions into its risk assessment with such news, consistent with theories of inattention to information. A real-options model is used to consider debt financing trade-offs associated with sovereign inaction or investment into adaptation.

Keywords: Climate change, sovereign risk, investor inattention, coastal flooding, climate adaptation.

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

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Approximately 780 million people in coastal zones are vulnerable to extreme sea levels, including waves, tides, and storm surges (Kulp and Strauss, 2019). Rising seas are doubling the likelihood of a large-scale flood every five years (Taherkhani et al., 2020), sparking concerns about financial stability (Carney, 2015) and losses for investors (Krueger et al., 2020). The capitalization of these risks can fiscally strain government debt servicing, weakening its capacity to absorb shocks as they materialize (Augustin et al., 2022). However, it is unclear if sovereign debt markets account for this risk (Brunetti et al., 2021), as studying market responses to these phenomena is methodologically challenging due to the limited time series variation of coastal surges and the slow-moving nature of sea level rise (SLR).

This paper determines whether sovereign credit markets incorporate expectations of coastal flooding and SLR. To overcome identification issues, I isolate a behavioral channel using a news index that proxies when information on these risks is particularly salient. This pricing mechanism is used to determine if investors update their beliefs on flooding and expected SLR hazards by embedding them into credit default swap (CDS) spreads. I find that the sovereign CDS market integrates publicly available information regarding flooding vulnerability, correctly differentiating between regions that are susceptible. Confirming this relationship between news and coastal flooding is necessary to determine if the market considers longer-term information—such as vulnerability influenced by SLR and demographic changes. I show that investors are slow to integrate climate and demographic projections, which have proven inaccurate compared to observed data. Additionally, I find that the market rewards large-scale investments into adaptation by applying no additional premium. This relationship allows for the assessment of the optimal timing of adaptation investment under expectations of SLR and coastal flooding risks.

Risk is assessed using sovereign CDS spreads, which have useful attributes for this setting: (i) CDS instruments function as insurance contracts protecting against default risk, (ii) they have standardized contracts over multiple time horizons, which are valuable in understanding risk expectations across various horizons and for cross-country comparisons (Augustin et al., 2020), (iii) they rapidly reflect new credit information (Gyntelberg et al., 2018), and (iv) they are more liquid than the underlying bond (Mullin and Bruno, 2020). For the empirical analysis, 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, akin to Hilscher et al. (2015).[1] This approach allows me to test whether risks are integrated with news and to assess the relevance of hazards across the term structure.

I begin by presenting evidence that the market capitalizes ex-ante coastal flooding vulnerability contemporaneously with greater news intensity, particularly for longer-term spreads. A one-standard deviation increase in the index results in a 62 and 73 basis point difference in 5- and 10-year CDS returns, respectively, between more and less vulnerable sovereigns. To understand the economic implications, government debt with 5- and 10-year maturities constitutes the bulk of sovereign obligations, totaling tens of billions annually (Arellano and Ramanarayanan, 2012). Assuming the CDS-bond basis holds, this premium increases interest expenditures by hundreds of millions over the debt's duration.

I estimate these effects using an identification strategy based on historically available vulnerability data to classify sovereigns into more and less vulnerable groups. I then conduct panel regressions, projecting CDS returns on a set of control variables, and include an interaction term between a news index and a vulnerability-based binary indicator. The coefficient on the interaction term represents the difference in returns between the two groups.

Data on vulnerability is collected from Vafeidis et al. (2011)—information cited by the Intergovernmental Panel on Climate Change (IPCC) (Nicholls et al., 2007) and widely distributed during climate summits such as the Conference of the Parties, as well as through news media.[2] Specifically, I use their measurements of the percentage of a country's population residing in the 1-in-100 year floodplain, as the metric is used in the economics, financial, and scientific literature (see Dell et al. (2012); Painter (2020); Hallegatte et al. (2013)), and is forecasted under different climate scenarios.[3]

Given that information on vulnerability is disseminated through these reports and amplified during climate conferences, I use the international summits news index developed by

[1]This period is selected post the CDS Big Bang and the Global Financial Crisis, and because SLR is being priced in other markets (Goldsmith-Pinkham et al., 2023).

[2]The IPCC has significantly influenced global climate policy, such as by proposing to limit the increase in global temperature to below 2 degrees Celsius. As an example, see `https://unfccc.int/resource/docs/2009/cop15/eng/11a01.pdf`.

[3]A "1-in-100 year" flooding event has a 1% chance of occurring in any given year and are a commonly used threshold in economics and climate literature (Gibson and Mullins (2020); Hallegatte et al. (2013)). I also crosscheck flood protection standards from Lincke and Hinkel (2018) and set vulnerability to zero if a country is protected from a 1-in-100-year flooding event.

Faccini et al. (2023) as a proxy for investor learning. I hypothesize that an increase in news intensity concerning climate summits indicates a reallocation of investors' scarce cognitive resources towards the prioritization of physical climate risks—a topic emphasized in IPCC reports and during climate summits. For example, Figure 1 illustrates the increase in SLR exhibited on the second pages of the IPCC's fourth and fifth assessment reports, issued in 2007 and 2014. Additionally, conference delegates often engage in attention-grabbing stunts to draw attention to climate change risks, which have been shown to shift credit risk (Kölbel et al. (2024); Ilhan et al. (2021)).[4]

I confirm this initial result with various robustness checks, which affirm the face validity of measuring vulnerability through population exposure and the synchronous relationship between news and risk pricing. First, I show that including confounders, such as transition risk, changes in adaptive capacity, temperature anomalies, precipitation, drought, and liquidity, do not alter this relationship. Second, I achieve similar results using other attention proxies. Third, I find that CDS premiums, extracted using the reduced-form credit model by Pan and Singleton (2008), are consistent with this pattern.

I next investigate if the market considers a related information set, the expected changes in coastal flooding hazard, measured by using forecasts of SLR and population growth developed in Vafeidis et al. (2011). The risk is material as the long-run compounding effects of coastal population growth and SLR exponentially increase the likelihood of damaging floods (Taherkhani et al., 2020). To assess expected changes, I estimate each sovereign's annual rate of change to coastal flooding by regressing its population vulnerable to 1-in-100-year floods on a linear time trend. These coefficients reveal cross-sectional variation, with some countries showing reduced risk due to inland population shifts. To denote exposure, I select countries vulnerable to coastal flooding and further split them into groups according to the sign and magnitude of the estimated rates of change. This indicator is then interacted with the news index to understand the relationship between CDS returns and expected vulnerability.

The empirical results indicate no significant difference in 10-year CDS returns between more vulnerable and less vulnerable sovereigns. What frictions might be preventing differen-

[4]For example, Naderev Sano held a hunger strike during the Warsaw Climate Conference in order to raise awareness of Hurricane Haiyin. Also, Tuvalu's foreign minister delivered a speech while standing knee-deep in flooded waters for the Climate Conference in Glasgow.

tiation between countries with adverse or more favorable SLR exposure trends? DellaVigna and Pollet (2007) develops a behavioral channel to suggest that investors and markets may overlook signals as the information is less-salient today. In this context, investors underreact to climate and demographic forecasts since SLR will exacerbate coastal surges only over the long-run. If this inefficiency stems from constraints of limited attention, I expect positive return predictability for sovereigns with adverse trends of SLR exposure.

To assess inattention to climate information, I conduct both in-sample and out-of-sample (OOS) predictability regressions. I find that the monthly OOS mean squared forecast error of rolling window estimations (Campbell and Thompson, 2008), yields R-squared values between 3 and 5 percent for more vulnerable sovereigns when using climate projections. These values do not reverse in the short run. The positive OOS R-squared values suggest that market participants are slow to incorporate expected changes in coastal flooding hazards, supporting a theory of underreaction to *information*.[5] It is important, however, to highlight the discrepancy between the expected and observed trends. Scientists and demographers in the early 21st century assumed that coastal populations would grow faster than inland populations, but recent evidence reveals this did not materialize Merkens et al. (2018). Taken together, the findings support three conclusions about the sovereign credit market: (i) a premium is ascribed to vulnerability to coastal flooding, (ii) the market is slow to incorporate expected changes in this hazard, and (iii) risks appear mispriced as the market embeds inaccurate climate model projections.

How should vulnerable sovereigns respond to this premium? My investigation into a subsample that adapted by building protections against 1-in-100-year coastal floods reveals that the market does not apply the same premium. Therefore, sovereigns face a decision between investing in protection or enduring the fiscal strain from increased interest payments and rising flood risks. I propose a real-options model featuring sequential irreversible investments into adaptive capital with stochastic bottlenecks (Oh and Yoon, 2020) and floods to consider optimal investment decisions under uncertainty. In essence, the model predicts that a "wait-and-see" strategy may be optimal for many vulnerable sovereigns.

[5] I emphasize that this result suggests an underreaction to the information being disseminated, not to the realized hazard itself.

This study contributes to the active body of research on climate change and sovereign risk, providing novel evidence that sovereign credit markets price expectations of coastal flooding and SLR risks. Considering that the majority of damages from climate change will occur in the future, Klusak et al. (2023) simulates how sovereign ratings may decrease under climate scenarios based on GDP loss from rising temperature. This paper is distinct in that it reveals whether markets are impounding medium to long-term risks today instead of anticipating how economies may adjust. This finding extends Painter (2020) and Goldsmith-Pinkham et al. (2023) to document the credit risk in an international asset class while separately considering vulnerability to coastal flooding and SLR. I also avoid using realized weather shocks due to the difficultly in disentangling expectations from climate damages ex-post. In fact, I show that the flooding premium is a unique source of climate risk compared to temperature (Dell et al., 2012; Boehm, 2022) and that country climate metrics used in the prior literature are insignificant (Cevik and Jalles (2022); Beirne et al. (2021)).

The paper also adds to the discussion on market beliefs by uncovering a behavioral climate risk channel across the term structure of sovereign CDS spreads. Others have used news or attention indices as mechanisms for markets to update their beliefs regarding climate risk (Choi et al. (2020); Engle et al. (2020); Ardia et al. (2020)).[6] Schlenker and Taylor (2021) and Severen et al. (2018) find that derivatives prices and agricultural land markets capitalize climate change expectations and forecasts. The evidence presented here suggests that the market discerns information on vulnerability, such as projections of SLR exposure, albeit slowly. This underreaction to news is similar to the evidence presented by Hong et al. (2019), who find that equity prices underreact to country-level trends in droughts.[7]

Lastly, this article relates to a nascent literature on adaptation finance, which has focused on the adaptation decisions of individuals (Fried, 2022; Van der Straten, 2023) and corporations (Pankratz and Schiller, 2024; Grover and Kahn, 2024). Adaptation is particularly salient here as sovereigns cannot relocate, making them reliant on sovereign debt for

[6] 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.

[7] Kim et al. (2015), Gande and Parsley (2005), and Cathcart et al. (2020) 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.

infrastructure funding. Here, I consider sequential investment into protection with construction delays as they are common for large-scale infrastructure projects (Majd and Pindyck, 1987; Oh and Yoon, 2020). Additionally, I incorporate a non-linear probability of coastal flooding shocks aligned with climate science. The sensitivity analysis offers policy recommendations for optimal investment timing under uncertainty, conditional on vulnerability.

The paper proceeds as follows. Section 1 develops the hypotheses. Data collection, sample creation, and exposure are calculated and described in Section 2. Section 3.1 presents empirical results relating attention to sovereign CDS returns, and Section 3.2 discusses market efficiency. The real-options model is detailed in Section 4 and robustness checks are in Section 5. I conclude in Section 6.

1 Hypothesis Development

I outline a 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 coastal flooding and SLR 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 λ. 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 τ_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 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 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.[8] 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. h ($h = 0, \ldots, H$) is a lag factor for how quickly this information is incorporated into CDS spreads, critical for the developing the hypotheses. α, β, θ, and ϕ are functions of the information included in the contemporaneous and lagged state variables.

The base hypothesis is motivated by prior 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 context, information regarding coastal flooding hazards becomes more salient and accessible to investors during climate summits. This heightened perception and saliency of hazards should lead markets to increase the credit risk for sovereigns with a substantial proportion of their population vulnerable to coastal flooding. Prior literature substantiates this hypothesis as Kölbel et al. (2024) and Ilhan et al. (2021) find that risk increases during summits. Moreover, short-term adaptation is infeasible as coastal defenses take decades to build.[9]

[8]Damages from storms, with storm surges being a considerable aspect, account for more than 60% of the damages attributed to climate change (Newman and Noy, 2023). Painter (2020) and Goldsmith-Pinkham et al. (2023) also demonstrate how flooding and SLR can elevate the risk of regional economies.

[9]The Delta Works in the Netherlands took four decades and $13 billion to complete, according to the New York Times article, "Lessons for U.S. From a Flood-Prone Land," published on November 14, 2012. Venice's flood barrier took slightly less than two decades to build.

Information on the vulnerability of sovereigns to coastal flooding is prevalent, publicly available, and does not require specialized knowledge of climate forecasts or trends. The information is also salient because, while the probability of a flooding event is low in any single year, the risk compounds over time to present a threat over the medium to long term. This assumption suggests that h will be close to zero and that C will be integrated into prices contemporaneously with news. Following this thread, I propose the following prediction:

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

Next, I outline how the market may consider incorporating longer-term risks, i.e., the changes in coastal flooding hazard. The 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). However, these long-term forecasts are less salient today, leading to limited attention to the information. This outcome aligns with the theory of DellaVigna and Pollet (2007), which suggests 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, leading 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 information.*

The prediction implies that CDS spreads are predictable when climate information is less salient, i.e., when $h > 0$. It suggests that the news index, which proxies for SLR hazard information entering the market, should positively predict CDS spreads for the most vulnerable sovereigns. 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 coastal flooding hazard and its changes 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.[10] 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,

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

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 information regarding climate hazards becomes more salient to investors during international summits, thereby updating their beliefs and influencing 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 information is disseminated during international climate summits. To capture the market's attentiveness to summits, 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 his representative country and hometown, Tacloban in the Philippines.[11] 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.[12]

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

[12] 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.

To represent global attention to climate summits and information being digested by the market, 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 2, 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 information absorbed 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. 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 sentiment expressed is positive, negative, or neutral. Intensity, on the other hand, measures the strength or magnitude of the discussion surrounding international summits.

To summarize, the index serves as a proxy for the level of attention investors pay to climate summits. The assumption is that information on climate risks becomes more salient during these periods because (i) the literature on risks is highly disseminated, and (ii) global attention towards SLR and coastal flooding hazards increases. Consequently, investors update their climate-related beliefs, leading to increased risk for relevant securities, as documented by Kölbel et al. (2024) and Ilhan et al. (2021).

2.3 Construction of Extreme Sea Level Vulnerability

Since the first objective of this paper is to understand whether the market incorporates coastal flooding, this section aims to measure vulnerability 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.[13]

To compute the this coastal flooding 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).[14] 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 numerous citations of Neumann et al. (2015). I define this measure as sovereign susceptibility to extreme sea level (*ESL*) hazard—a term commonly used in contemporary climate science (Gregory et al., 2019).

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

[13]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.

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

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 vulnerability for Hong Kong, Israel, Italy, Qatar, Bahrain, and the Netherlands to zero as they are protected against such disasters.

The 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 based on their percent of exposure; these can be identified as the third column of each panel in Table 2.

For the empirical identification strategy, I use a methodology that sorts sovereigns into "more-" and "less-vulnerable" 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 9.4, 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 expected population growth and sea level rise (SLR)—what I term ΔESL hazard. I calculate country-specific trends in vulnerability by evaluating forecasted trends based on SLR and population forecasts developed by Vafeidis et al. (2011) and Neumann et al. (2015).

I focus on a subset of sovereigns vulnerable to *ESL* hazards, specifically those in the fourth quartile 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 quartiles are not included when assessing whether the credit market incorporates ΔESL 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 use data from Vafeidis et al. (2011) and Neumann et al. (2015). Instead of using their baseline 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 and ending in 2060 under four socio-economic scenarios (A through D), all of which assume faster population growth on the coast than in the interior.[15] 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 rising seas, which would subsequently expand the area of the 1-in-100-year floodplain and increase the number of people affected.

[15] While more recent literature by Merkens et al. (2018) 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.

In order to evaluate whether a sovereign is expected 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 λ for the year t as follows:

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

where the estimated λ 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 years 2030 and 2060. 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, λ, for the 14 sovereigns with a baseline vulnerability to *ESL* hazard. Figure 3 illustrates the values of the estimated λ 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 λ to obtain the "more-" and "less-vulnerable" groups. These groups are visualized above and below the black dashed line in Figure 3.

In essence, the λ values represent the expectations of SLR vulnerability based on the climate science in the early 21st century. This information was disseminated through the IPCC 4rd and 5th assessment reports which are frequently used at the basis of negotiations during international climate summits. More recent advancements, however, have improved projections of population dynamics for global coastal impact assessments. As highlighted by Merkens et al. (2018), contemporary population growth projections indicate that approximately half of the sovereign nations are experiencing more rapid growth inland compared to their coastal regions. This tension suggests that the information disseminated between 2007 (IPCC's 3rd report) and 2023 (IPCC's 6th report) largely consisted of this false assumption. In Section 9.5, I provide details on how I calculate historically accurate trends in exposure.

Overall, this approach allows for the separation of *ESL* and ΔESL 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 ΔESL 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 News Intensity

3.1.1 Vulnerability to Extreme Sea Levels

The key identification assumption is that the international summits index serves as a proxy for investor attention to coastal flooding risk and SLR, inducing exogenous changes in investors' information processing choices. To test whether the sovereign credit market incorporates *ESL* hazard with news intensity covering climate summits, i.e., the first hypothesis, I use sovereign CDS returns to capture changes in market risk and CDS spreads. 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:

$$R^{SCDS}_{i,t+1} = \frac{\Delta s_{i,t+1}}{s_{i,t}}. \quad (5)$$

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, $Vulnerable$, that denotes whether a country is vulnerable to *ESL* hazard. Specifically, $Vulnerable$ is assigned a value of 1 for countries deemed vulnerable and 0 for those considered less vulnerable. This indicator is subsequently interacted with *Attention* to estimate the difference in the relationship between attention and sovereign CDS returns between the country cohorts. I include regional clustering to account for serial correlation of the error term (Abadie et al., 2017) within each sovereign and winsorize returns at 1%. The estimated regressions follow the format:

$$
\begin{aligned}
R^{SCDS}_{i,t+1} = \alpha + \beta_1(Vulnerable_i \times Attention_t) + \beta_2 Attention_t \\
+\beta_3(CO2_{i,t} \times Attention_t) + \beta_4 CO2_{i,t} \\
+\beta_5(Temperature_{i,t} \times Attention_t) + \beta_6 Temperature_{i,t} \\
+\gamma \Delta X_{i,t} + \eta_i + \rho_{i,t_y} + \varepsilon_{i,t},
\end{aligned} \tag{6}
$$

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.

In addition to highlighting coastal risks, international summits also serve to emphasize other climate issues such as rising temperatures and greenhouse gas emissions, as illustrated in Figure 1. To account for these confounders, I interact changes in yearly CO2 emissions per capita (emissions intensity) with *Attention* as measure of transition risk for each country.[16] Additionally, I include monthly temperature anomalies that are aggregated to the sovereign level and are interacted similarly. 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.

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

[16] These are risks associated with the process of transitioning from a carbon-intensive, fossil-fuel-based economy to a low-carbon economy.

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.

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 η_i represents country-by-month fixed effects to capture seasonal unobserved country heterogeneity that may affect sovereign CDS spread returns. ρ_{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.

In this specification, β_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 $Vulnerability$. In line with hypothesis H_1, I expect the coefficient of interest, β_1, to be significantly greater than zero for medium- to long-term sovereign CDS tenors, 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 approximate the information available to the market and mitigate measurement error in calculating sovereign exposure, I rely 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 vulnerable sovereigns, and the second and first quartiles are the least vulnerable to *ESL* hazard. This method places the 14 most vulnerable countries into a single "more vulnerable" category, and the other 30 into the "less vulnerable" 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. Furthermore, the larger sample size reduces the standard errors of the coefficient estimates. To allay concerns of spurious correlations introduced due to the sorting choice, I conduct placebo tests by randomly assigning sovereigns to different quartiles in Section 9.0.1. There, I show a Gaussian distribution of β_1 to confirm the robustness of the results against the potential noise induced by arbitrary sorting.

Table 4 presents the estimates from regressing the 1-, 5-, and 10-year sovereign CDS returns of sovereigns against the attention index. The first row presents the coefficient of interest, i.e., the additional effect of news intensity on the CDS returns of sovereigns more vulnerable to coastal flooding. I find that the relationship between news and the 5- and 10-year returns for the more exposed sample are significant at the 10% and 5% level, respectively. Specifically, the effect of a one-standard-deviation increase in the attention index is associated with a difference of 0.62% and 0.73% 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.

In columns 4, 5, and 6 of Table 4, I include additional interactions by pairing each country's CO2 emissions per capita and temperature anomalies with the news index. The analysis reveals that temperature anomalies increase sovereign risk in the absence of media attention, confirming the findings of Boehm (2022). Carbon emissions intensity does not significantly influence CDS returns.

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.

The findings provide robust evidence that sovereign CDS returns for ESL-afflicted sovereigns are contemporaneously associated with global attention to information disseminated during climate summits, and by implication, coastal flooding vulnerability. 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) use 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 vulnerability is incorporated, I perform a set of robustness checks that further confirm these results. In Section 5.1, I include total monthly precipitation and drought as additional control variables. Moreover, I show that incorporating changes in country level infrastructure, climate adaptation, and aggregate exposure leaves the magnitude and direction of the estimated relationship unchanged. Indeed, I find no significant impact of these metrics on sovereign risk, which marks an important difference between my findings and those in the prior literature (see Cevik and Jalles (2022) and Beirne et al. (2021)). In Section 5.2, 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 9.4 demonstrates that using alternate data from the 2000s yields consistent results. In Section 10.1, 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 9.1). Moving to Section 9.2, I use an alternative country-level attention index—Google Trends data on "UN Climate Change Conferences"—and uncover a congruent effect on CDS returns.

3.1.2 Changes in Extreme Sea Level Hazard

In this section, I conduct empirical tests to study whether the credit market is incorporating information on country-level changes in ESL vulnerability. The goal is to examine whether hypothesis H_2 holds for a hazard manifesting over a longer time scale. Consequently, only 10-year spread returns are selected as the dependent variables, as ΔESL is only relevant at these longer timescales.

I use a set of sovereigns that are vulnerable to ESL hazards, specifically those in the fourth quartile 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. 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, λ_s, using climate and demographic projections, as outlined in Section 2.4. Figure 3 highlights the substantial heterogeneity in vulnerability to ΔESL hazard that the projections produce.

I present the estimates for the groups of sovereigns that are more- or less-exposed to ΔESL hazard in Table 5. 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 implies that the market does not price ΔESL hazard *contemporaneously* with climate news. This result supports hypothesis H_2 in that the hazard is unpriced as information on SLR is slow to be processed by the market; however, further empirical tests have to be performed in order to see whether there is an underreaction to the information being disseminated.

The main results presented here use an equally weighted forecast across all four population and SLR scenarios denoted in Neumann et al. (2015). To check whether the market follows a certain scenario, I re-sort sovereigns based on individual scenarios and find that the grouping remains identical. Additionally, in Section 10.1, I perform a robustness check that further confirms the return response pattern I find here. Again, I use the decomposed risk premiums for 10-year sovereign CDS spreads and regress this on the interaction terms. Table 17 shows that there is no significant difference between groups of sovereigns.

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 investors are prone to overlooking long-term signals and demographic changes that are less salient when information is disseminated (DellaVigna and Pollet, 2007). In the context of processing forecasted information, the market may simply be neglecting the projections concurrently with information and incorporating the information in a laggard fashion. This friction would result in a delayed market reaction, in that lagged climate information (proxied by news) would positively predict the CDS returns for the more vulnerable sovereigns under forecasts. In the next Section, I find evidence that the market gradually incorporates information on ΔESL from climate and demographic models asynchronously with attention.

These nuanced findings help reconcile the mixed results observed in prior literature by observing differentially priced information sets. Murfin and Spiegel (2020) conclude that future property inundation, inferred from historical data, is not priced in residential real estate markets. In contrast, Nguyen et al. (2022) uncovers a SLR premium and increased default probability for affected residential properties.

3.2 Market Efficiency

I next show that sovereign CDS returns for countries exposed to ESL, and particularly ΔESL hazard, are predictable when using the climate summit news index. This predictability suggests that the market is sluggish in pricing coastal flooding and SLR exposure as information is processed by the market, 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 predictability in prices or returns. 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 9.3, show that the second lag of the index is significant in predicting CDS returns for more vulnerable sovereigns, with no reversal observed at the third lag. 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 (OOS) regressions as the highest standard for predictability, as they mirror the real-time situation of investors. [17]

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 approaches to collapse the returns for each exposure group on the basis ΔESL: (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

[17] 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.

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^TX. The first principal component, the vector containing the greatest sample variance for all linear combinations of X, is obtained as:

$$z_{t,1} = Xv_{t,1}, \tag{8}$$

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 ΔESL 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 both the first and second-period lag of the climate summit attention index as the predictor variables, since the results in Section 9.3 indicate significant in-sample predictability for the second lag. To test the degree of OOS predictability, I use the R^2_{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 is outlined as follows:

$$R^2_{\text{OS}} = 1 - \frac{\sum_{t=T_1}^{T}\left(r_t - \hat{r}_{\text{t}|t-(1,2,3)}\right)^2}{\sum_{t=T_1}^{T}\left(r_t - \bar{r}_{\text{t}|t-1}\right)^2}, \tag{9}$$

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 either $t-1$, $t-2$, or $t-3$. $T1$ 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_{OS} greater than 0.5% represents an economically valuable predictor.

I present the R^2_{OS} values in Table 6. These values are obtained from rolling windows of either 42 months or 54 months in order to demonstrate robustness of the results. Panels (a) through (c) present results using the first, second, and lag of the index. 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_{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 adjusted for 3 lags.

Across all columns, return predictability is greatest for the group of sovereigns with higher vulnerability to ΔESL when using the 2nd lag, consistent with the PVAR results. The R^2_{OS} statistics are economically meaningful, ranging from 2 to 5, and are significant at the 5% level. In contrast, the OOS tests for sovereigns less vulnerably show no significant predictability. These results imply that the market is gradually trading on projected rather than observed information. 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.

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 more salient than information on long-term climate and population projections. Therefore, in the following months, the market prices ΔESL risk and slowly incorporates the relevant information—suggestive of limited attention towards changes in SLR vulnerability supporting hypothesis H_2. A potential theoretical explanation for this anomaly is consistent with theories of limited investor attention, aligning with the theoretical model and findings of DellaVigna and Pollet (2007), who identify market inattention to demographic trends relevant in the future.

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 assimilates expectations of climate trends. However, a critical 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* ΔESL 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 Real-options framework

Through the empirical tests, I confirm a greater interest burden for sovereigns vulnerable to coastal flooding and SLR. Besides raising debt financing costs, climate shocks can erode productive capacity by damaging physical and human capital. Post-disaster, governments increase public spending for emergency relief and infrastructure repairs (Deryugina, 2022). The combination of risk premiums demanded by investors and the increased issuance of public debt due to flooding events exacerbates sovereign debt obligations, potentially straining fiscal budgets for non-U.S. sovereigns (Blanchard, 2019). Furthermore, an elevated debt burden undermines a sovereign's resilience to future climate shocks (Augustin et al., 2022).

A strategic response to mitigating these negative consequences involves investment, as Section 5.3 demonstrates that sovereigns invested in adaptive infrastructure against 1-in-100-year floods avoid such premiums. While adaptation appears increasingly necessary due to inadequate global efforts to close the emissions gap—potentially leading to a 3.1°C temperature rise—sovereigns face uncertainty in their decision to adapt, owing to fiscal costs, routine delays, and overruns in public infrastructure projects, which impact debt sustainability.[18] However, limited research has examined the trade-offs between financing adaptation and enduring flooding vulnerability. Prior literature has primarily studied adaptation at the corporate (Pankratz and Schiller, 2024), household (Fried, 2022), and political levels (Van Der Straten et al., 2024), or through financial markets (Kahn et al., 2024).[19]

4.1 Model

The benefits of adaptation are twofold: (i) building protective measures reduces the interest rate burden on the sovereign, and (ii) it helps defend against damages, thereby lowering the need for post-disaster aid in the form of additional debt. Given that the empirical analysis focuses on debt premiums, and balancing government borrowing costs is a critical aspect of fiscal policy, I propose a real-options framework that minimizes the expected present value (EPV) of a vulnerable sovereign's interest payments. I model a discrete-time economy that is limited to debt issuance, featuring sequential irreversible investments (Majd and Pindyck, 1987) and stochastic bottlenecks (Oh and Yoon, 2020), characteristic of large-scale infrastructure projects. The sovereign exogenously issues numéraire debt every period and experiences stochastic damages in the form of coastal floods which spur additional debt issuance in the form of disaster relief.[20] Sovereigns may also initiate infrastructure projects for flood protection by issuing additional debt beginning in any period.[21] However, the project may stall, incurring additional costs and extending time to completion. The sovereign is burdened with the additional risk premium on its debt before the project is completed, reducing to the social discount rate after completion. As the model focuses on interest payments and not tax revenues, the sovereign simply rolls over its debt due to its inability to raise funds. Lastly, while climate shocks also affect government revenues and GDP growth (Ferreira, 2024), incorporating these factors requires further assumptions beyond the scope of my empirical analysis.

The sovereign, vulnerable to coastal flooding and SLR, operates over a planning horizon

[18]See the UN's latest report on the emissions gap `https://www.unep.org/news-and-stories/press-release/nations-must-close-huge-emissions-gap-new-climate-pledges-and`.

[19]For a comprehensive review on adaptation, see Ferreira (2024).

[20]This is a simplification as disaster relief will typically only cover a fraction of the initial damages.

[21]Examples of infrastructure investments in coastal flooding protection financed mainly by public debt include the Netherlands' Deltaworks (Bos and Zwaneveld, 2017) and Italy's MOSE project (Bank, 2024).

of T, issuing numéraire debt X exogenously each period. Debt evolves with the process $D_t = D_{t-1} + \text{Debt Issuance}_t$. At the start of each period t, debt issuance is given by:

$$\text{Debt Issuance}_t = X + C_t + F_t + \begin{cases} 0, & \text{if } t < s + L_{\text{actual}}, \\ U_t, & \text{if } t \geq s + L_{\text{actual}}, \end{cases} \tag{10}$$

where C_t denotes construction costs starting at time s and ending at L_{actual}, after which an upkeep cost is applied, U_t. Let F_t denote disaster relief proportional to the sovereign's vulnerability, with additional debt f, a fraction of the numéraire. The total extra debt from flooding events in period t is $F_t = X \cdot f \cdot N_t$, where $N_t \sim \text{Poisson}(\lambda(t))$ is the number of events. Here, flooding occurrences follow a Poisson process with a time-varying rate to capture increasing risk from sea-level rise. The rate function is $\lambda(t) = \lambda_0 \cdot 2^{\frac{t}{5}}$, where $\lambda_0 = 0.01$ is the probability of a 1-in-100 year flood event at time zero, consistent with Taherkhani et al. (2020).

The sovereign may choose to initiate construction of protective infrastructure at period s. Construction is planned to take L_{plan} periods but may be delayed due to bottlenecks, resulting in an actual construction time $L_{actual} \geq L_{plan}$. The construction cost per period is $C_t = X \cdot c$, where c is a fraction representing the construction cost relative to X. Each construction period, there is a bottleneck probability p_b, represented by a Bernoulli random variable B_t:

$$B_t = \begin{cases} 1, & \text{with probability } p_b, \\ 0, & \text{with probability } 1 - p_b. \end{cases}$$

Construction advances to the next period only if $B_t = 0$ and is stalled if $B_t = 1$. The government issues debt, C_t, throughout construction, including during bottleneck delays, reflecting project cost overruns. The total construction cost C_{total} is therefore: $C_{\text{total}} = \sum_{t=s}^{s+L_{\text{actual}}-1} C_t = X \cdot c \cdot L_{actual}$. After construction is completed at time $s + L_{\text{actual}}$, an upkeep cost per period U_t is applied, representing a fraction of the total construction cost.

For illustration, Figure 5 presents an example path of this process. The sovereign issues debt at a rate of $r \cdot$premium before construction completion, and (r) afterward. Construction starts at (s) with an intended completion time of 10 years (L_{plan}); however, the bottleneck extends the duration to L_{actual}. The dash-dot gray line shows the exponential increase in flooding, with floods indicated by patterned rectangles occurring as a Poisson process, allowing multiple events per period.

Next, I describe the evolution of interest rates on the issued debt. Because the empirical results focus on returns, I apply a risk premium multiplier m to the interest rate before the protection is built. The higher interest rate i_t persists until construction is completed and is given by:

$$i_t = \begin{cases} r \cdot m, & \text{if } I_t = \text{Incomplete if } t < s + L_{\text{actual}}, \\ r, & \text{if } I_t = \text{Complete if } t \geq s + L_{\text{actual}}. \end{cases}$$

where r is the social discount rate and I_t is infrastructure status. The Expected Present Value of interest payments can now be defined as a function of the decision variable s, i.e., the start time of building construction:

$$\text{EPV}(s) = \sum_{t=1}^{T} \left(\frac{1}{(1+r)^t} \cdot \mathbb{E}\left[D_{t-1} \cdot i_t\right] \right),$$

where the sovereign pays interest $i_t \cdot D_{t-1}$ on existing debt.

In the context of this real-options framework, the Bellman equation captures the trade-off between incurring immediate construction costs to reduce future flood- related costs and risk premiums versus waiting and potentially facing higher future expenses. At each time t, the government aims to minimize the expected present value of future interest payments by choosing the optimal action a_t from feasible actions $\mathcal{A}(I_t)$:

$$V(D_t, I_t) = \min_{a_t \in \mathcal{A}(I_t)} \left\{ i_t \cdot D_{t-1} + \frac{1}{1+r} \cdot \mathbb{E}\left[V(D_{t+1}, I_{t+1}) \mid D_t, I_t, a_t\right] \right\}.$$

Here, $V(D_t, I_t)$ is the value function representing the minimum expected present value of future interest payments starting from period t, given the current debt D_t and infrastructure state I_t.

4.2 Simulation and policy implications

I calibrate the model parameters informed by two prominent infrastructure projects that provide flooding protection for their respective regions—the Netherlands Delta works (Bos and Zwaneveld, 2017) and Italy's MOSE project (Giupponi et al., 2024). These projects serve as effective benchmarks due to their predominant reliance on government debt financing, compounded by notable construction delays and cost overruns, while effectively mitigating unprecedented flood risks.

Table 7 presents the baseline model parameters. The planning horizon is set at 50 years, aligning with projections of approximately nine floods annually due to SLR dynamics (Taherkhani et al., 2020). The premium multiplier is fixed, drawn from a two standard-deviation increase in news per empirical findings. Construction costs, along with additional debt for recovery and upkeep expenses, are modeled as a proportion of annual debt issuance. Analysis of the Deltaworks projects suggests that projects incur costs ranging from 1.8% to 7.4% of GDP of a single year (Bos and Zwaneveld, 2017). The MOSE project's costs exceeded six million euros over 17 years, accounting for about 25% of Venice's GDP in 2015, translating to an annual average of approximately 1.5% (Giupponi et al., 2024). Additional debt issuance per period therefore ranges from 1% to 7%, reflecting substantial investment needs for some sovereigns. I assume a 10-year construction duration with upkeep costs at 1% of total project costs.[22] The Delta Works and MOSE projects required approximately an additional decade to complete than originally planned. Based on these delays, I estimate a bottleneck probability of 41%, i.e., the average of the two projects using the methodology outlined in Oh and Yoon (2020).[23]

I use a Monte Carlo approach to provide intuition on the time-to-investment (TTI) across various scenario. First, simulations determine the EPV of interest payments across different start times and parameter combinations, generating strategies that represent optimal start times for each states of the world. Second, random events such as floods and

[22] MOSE's maintenance costs are estimated at 80 million euros, 1.33% of the total cost. See https://www.italymagazine.com/featured-story/venices-flood-barriers-project-mose-activated-first-time.

[23] Oh and Yoon (2020) estimate bottleneck probability using $1 + \frac{\bar{K}-1}{1-p_b}$, where $\frac{\overline{K}}{\kappa}$ is the planned completion period without bottlenecks, assuming optimal resource use.

construction delays are simulated across varying parameter values. By selecting optimal decisions from the computed strategies, I evaluate their performance under these simulations.

I use a finite differences approach to provide an approximation of the derivative of the EPV function with an increment of 0.01 for the parameters of interest. Figure 4 presents the comparative statics at various points in time for investment using a fixed 4% discount rate for four parameters: bottleneck probability, construction cost, extra debt due to damages, and the premium multiplier. The EPV is sensitive to all the parameters of interest, although, the bottleneck probability has a minimal effect on the present value of cumulative interest payments over the long term. If construction begins immediately, the associated costs weigh heavily in the present value calculation due to early incurrence and minimal discounting. Conversely, delaying construction results in continued premium payments as the market maintains its risk premium, dominating the other parameters after a decade. Flood-related damages moderately influence the EPV, increasingly with probability of flood incidents over time.

Next, I assess the average TTI while varying the discount rate, construction costs, flood damages, and premiums, keeping the bottleneck probability fixed at 41%. The colored bands in Figure 6 represent the year that minimizes interest payments across the planning horizon. Using these Figures, I examine the relationship between each parameter and the sovereign's decision to invest in adaptation capital.

Despite the lack of consensus in climate economics and finance on the appropriate discount rate for public investments (Giglio et al., 2021), Gollier and Hammitt (2014) suggests a range of 1% to 4%. Generally, the panels in Figure 6 show that higher discount rates postpone investments by demanding economic returns that cover higher capital costs. Nonetheless, the figures reveal considerable latitude in rates, with only minor effects on TTI when holding exposure or construction costs constant. Sovereigns with tighter borrowing conditions should time investments for periods of lower debt rates to offset timing constraints.

Panel (a) in Figure 6 suggests a large option value in flexible construction costs, as lower costs expedite TTI. While MOSE's costs reached 1.5% of Venice's GDP annually under poor management, Delta Works, more efficiently managed, required less than 0.5% of the Netherlands' GDP per year. Under these conditions, TTI remains below a decade for these developed economies. In panel (b), I compare damage to construction costs for less vulnerable sovereigns, holding the discount rate at 4%. These parameters are realistic, as many sovereigns fall within this range, and infrastructure likely serves smaller areas. The model suggests that maintaining construction costs below 3% of debt accelerates TTI, a feasible condition for lower-middle-income economies like Egypt, but challenging for those with stringent borrowing constraints.

Panel (c) reveals that increased exposure accelerates the TTI decision when holding construction costs at 5% per period. Given that the empirical sample begins in 2010, the optimal window for initiating construction projects may have closed for some sovereigns, such as Egypt, where more than 10% of the population is susceptible to 1-in-100-year flood events. For less vulnerable sovereigns, delaying investment remains a viable option, provided they begin within two decades.

Finally, I show in panel (d) that a greater premium on coastal flooding and SLR would incentivize sovereigns to rapidly invest in adaptation capital. Together, the sensitivity analysis implies that low construction costs, greater premiums, and higher damages bring forward the TTI. Investment into adaptation capital should be a priority for sovereigns that are effectively able to keep construction costs below 3% of their economy per period. Credit constrained countries such as Bangladesh will require substantially lower terms of borrowing to expedite TTI. Therefore, multilateral agreements, discussed frequently during climate conferences, should aim to alleviate credit constraints for the most vulnerable nations.

5 Auxiliary Empirical Tests

5.1 Controlling for Other Confounders

Other climate risks given attention during international summits could potentially confound the estimated relationship. To account for this, I use 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 the yearly changes in three indices: human exposure to climate risks, national infrastructure vulnerability, and the readiness of a country to adapt to climate change. To control for other physical risks, I also include total monthly precipitation and average monthly drought experienced by each country. This section demonstrates that incorporating these additional indices does not alter the original relationship between international summits and sovereign CDS spreads.

Table 8 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.

Overall, I confirm that coastal flooding risk is priced with greater attention to summits and increased information saliency, even after controlling for ex-post risks, infrastructure, and climate readiness.

5.2 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 β. I estimate three latent factors for each group of sovereigns (unexposed and exposed to *ESL* hazard) between January 2010 and stop at December 2017 to mitigate look-ahead bias. This factor explains 63% of the variance for the unexposed sample and 70% for the exposed sample, respectively.

The time period selected for estimating β's is from 36 to 260 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.[24] 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 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 α_i and β_i. Abnormal returns are then calculated by subtracting realized returns during the event window by expected returns as follows:

$$AR_{\mathrm{i,t}} = R_{i,t}^{SCDS} - (\alpha_{\mathrm{i}} + \beta_{1,\mathrm{i}} f_{1,\mathrm{t}} + \beta_{2,\mathrm{i}} f_{2,\mathrm{t}} + \beta_{3,\mathrm{i}} f_{3,\mathrm{t}}), \tag{11}$$

where f_1 represents the first principal component, $\beta_{1,\mathrm{i}}$ through $\beta_{3,\mathrm{i}}$ are the estimated coefficients from the historical period, and $AR_{\mathrm{i,t}}$ is the abnormal return for a time period in the event window.

Figure 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 1.4% four weeks after October 29, peaking in the first week of COP21. The economic magnitude of the relationship is in line with the prior findings that showed a 73 basis point increase in spread returns 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. T-tests confirm a significant

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

difference in the abnormal return series between the two exposure groups for various event windows such as [-2,4], [0,4].

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.

5.3 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.[25] 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 11. 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 12 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

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

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.

6 Conclusion

In this paper, I show that the sovereign credit market incorporates expectations of coastal flooding and sea level rise (SLR) vulnerability into credit default swap spreads. Specifically, I use data on vulnerability to provide evidence that the CDS returns for inundated sovereigns are increasing in comparison to less vulnerable nations when information, proxied by a news index, becomes more salient.

I find that the market also prices expected vulnerability of sovereigns based on climate forecasts of population growth and SLR. However, this pricing occurs gradually, indicating the presence of market frictions in incorporating climate information. Specifically, the returns on credit spreads for sovereigns exposed to changes in extreme sea level hazards are predictable when using the same news index.

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. To provide intuition on adaptation policy, I study a model where sovereigns have an option to invest into large-scale infrastructure to alleviate fiscal constraints. However, the sovereign faces stochastic bottlenecks and coastal flooding shocks. By calibrating the model with well-known projects, I demonstrate that the ideal time to start investing in adaptation has likely not yet arrived for many sovereigns. 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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7 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.
ΔESL 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.

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

This table shows the percentage of a sovereigns'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 rightmost column of both panels represent the quartile of exposure to *ESL* hazard.

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

Table 3: Sample Statistics

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. Temperature anomaly refers to the average maximum temperature deviation for a country in a given month, as sourced from Berkeley Earth. Drought represents the average Palmer Drought Severity of the country in a month. CO2 per capita is at the yearly frequency and obtained from Climate Watch.

	Mean	SD	p25	p50	p75	N
% Δ 1 Year Sovereign Spread	3.538	38.223	-14.459	-0.276	12.998	7021
% Δ 5 Year Sovereign Spread	0.159	13.273	-7.030	-0.469	4.825	7021
% Δ 10 Year Sovereign Spread	0.177	10.498	-5.114	-0.405	3.624	7021
MSCI Local Returns	0.135	6.437	-3.538	0.045	3.884	7015
MSCI Vol	7.556	47.937	-22.192	-1.629	24.616	7015
% Δ International Currency Reserves	18.372	1494.622	-1.291	0.209	1.901	7021
% Δ Exchange Rate Dollar	0.286	2.286	-0.678	0.001	1.075	7021
% Δ Debt to GDP	0.303	1.412	-0.202	0.169	0.674	7021
1 Year CDS Gamma	-0.048	0.240	-0.196	-0.040	0.107	7021
5 Year CDS Gamma	-0.019	0.243	-0.165	-0.013	0.145	7021
10 Year CDS Gamma	-0.029	0.244	-0.172	-0.020	0.132	7021
Temperature Anomaly	3.474	1.936	1.764	3.690	5.017	7021
Drought	-0.304	1.608	-1.405	-0.224	0.802	7021
Google Trends	2.621	-7.285	0.000	0.000	3.000	6844
% Δ Log Gross Notional Amount	-0.533	6.542	-3.507	-0.589	2.157	3545
Oxford Economics Credit Rating	13.379	4.287	10.500	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
CO2 Per Capita	6.504	5.519	2.885	5.432	7.968	580
% Δ VIX	1.971	24.552	-14.601	-2.269	10.851	118
% Δ 5 Yr Treasury	0.307	11.680	-6.637	0.000	5.789	118
% Δ FTSE Bond Index	0.164	1.547	-0.921	0.185	1.296	118
SPX Returns	0.978	3.598	-0.750	1.395	3.030	118
International Summits	0.289	0.183	0.138	0.256	0.404	118

Table 4: Impact of news on sovereign CDS returns conditional on vulnerability to extreme sea levels

This table reports the regressions that relate news on international climate summits to sovereign CDS returns at 1-, 5-, and 10-year maturities for countries vulnerable to extreme sea level (ESL) hazards. *Vulnerable* is equal to one when referring to the group of sovereigns in the fourth quartile of Table 4, and zero when referring to those in the first and second quartiles. The coefficient in the first row represents the interaction between the news index and *Vulnerable*, representing the differential impact on CDS spreads between vulnerable groups. ESL hazard is obtained from Vafeidis et al. (2011) who calculate the percentage of a population at risk from 1-in-100 year coastal floods. The $InternationalSummits$ index from Faccini et al. (2023) measures media attention to climate summits. Changes in yearly carbon intensity is obtained from Climate Watch and abnormal temperatures from Berkeley Earth. 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 ***, **, *.

	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
Vulnerable × International Summits	2.186	3.435*	4.030**	2.316	3.582*	4.120**
	(3.404)	(1.903)	(1.570)	(3.390)	(1.981)	(1.639)
International Summits	1.491	0.415	0.416	3.120	1.628	0.653
	(1.809)	(0.930)	(0.833)	(2.686)	(1.505)	(1.311)
Carbon Intensity				8.983	3.205	2.687
				(12.061)	(3.959)	(3.540)
International Summits × Carbon Intensity				-15.445	2.173	3.379
				(28.603)	(11.334)	(10.598)
Temperature				0.941	0.843***	0.567***
				(0.644)	(0.241)	(0.179)
International Summits × Temperature				-0.651	-0.546	-0.234
				(0.588)	(0.340)	(0.258)
SPX Returns	-1.577***	-0.839***	-0.674***	-1.568***	-0.835***	-0.671***
	(0.186)	(0.075)	(0.063)	(0.186)	(0.076)	(0.063)
MSCI Local Returns	-1.132***	-0.518***	-0.382***	-1.130***	-0.517***	-0.381***
	(0.150)	(0.064)	(0.049)	(0.150)	(0.064)	(0.049)
MSCI Vol	0.024***	0.012***	0.009***	0.024***	0.012***	0.009***
	(0.009)	(0.004)	(0.003)	(0.009)	(0.004)	(0.003)
FTSE Bond Index	-1.057***	-0.458***	-0.393***	-1.075***	-0.470***	-0.400***
	(0.321)	(0.115)	(0.100)	(0.321)	(0.115)	(0.101)
Exchange Rate Dollar	0.310	0.331**	0.213*	0.304	0.321*	0.204*
	(0.265)	(0.159)	(0.119)	(0.266)	(0.160)	(0.119)
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	0.093**	0.014	-0.006	0.095**	0.017	-0.004
	(0.036)	(0.012)	(0.010)	(0.037)	(0.012)	(0.011)
VIX	-0.021	-0.009	-0.010*	-0.020	-0.008	-0.010
	(0.024)	(0.008)	(0.006)	(0.024)	(0.008)	(0.006)
SovereignxMonth	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adj R Squared	0.307	0.381	0.355	0.307	0.383	0.357
Observations	5088	5094	5086	5088	5094	5086

Table 5: Impact of news on sovereign CDS returns conditional on vulnerability to changes in extreme sea levels

This table reports the regressions that relate news on international climate summits to 10-year sovereign CDS returns for countries vulnerable to changes in extreme sea level hazard. The International Summits index from Faccini et al. (2023) measures media attention to climate summits and is interacted with *Vulnerable* to produce the first-row coefficients, indicating the differential impact on CDS spreads between vulnerable groups. To calculate ΔESL, I begin with the 14 most exposed sovereigns to coastal flooding (fourth quartile, Table 4). ΔESL 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). Sovereigns are split into more- (1) and less-vulnerable (0) groups, represented by *Vulnerable*, based on whether a sovereign's trend coefficient is above or below the median across the 14 sovereigns. Splits are shown in Figure 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. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

	(1) 10 Year	(2) 10 Year
Vulnerable × International Summits	-4.208	-3.830
	(2.767)	(2.745)
International Summits	6.211**	5.992
	(2.457)	(3.468)
Carbon Intensity		7.618
		(6.399)
International Summits × Carbon Intensity		-12.793
		(14.740)
Temperature		0.747*
		(0.371)
International Summits × Temperature		-0.190
		(0.712)
SPX Returns	-0.794***	-0.793***
	(0.095)	(0.095)
MSCI Local Returns	-0.419***	-0.416***
	(0.079)	(0.078)
Debt to GDP	-0.040	-0.043
	(0.421)	(0.411)
MSCI Vol	0.006	0.007
	(0.006)	(0.006)
FTSE Bond Index	-0.265	-0.277
	(0.211)	(0.215)
Exchange Rate Dollar	-0.010	-0.027
	(0.135)	(0.136)
Intl Reserves	0.000***	0.000***
	(0.000)	(0.000)
5 Yr Treasury	-0.008	-0.004
	(0.023)	(0.025)
VIX	-0.028*	-0.028*
	(0.014)	(0.013)
SovereignxMonth	Yes	Yes
Rating	Yes	Yes
Adj R Squared	0.240	0.242
Observations	1620	1620

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

This table presents out-of-sample return predictability results using the first, second, and third lag of the news index as the predictor and a time-series of sovereign CDS returns as the predicted variable. The values presented in panels (a) through (c) are the R^2_{OS} developed by Campbell and Thompson (2008). The R^2_{OS} values are calculated based on the rolling months as described in the column titled "Rolling Months". The starting sample of sovereigns in all panels consist of the of the 14 sovereigns more exposed to *ESL* hazard, described as the fourth quartile in Table 4. 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. Then, sovereigns are split into more- and less-vulnerable groups based on whether a sovereign's trend coefficient is above or below the median, denoted in Figure 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 three lags as the considered autocorrelation structure. Significance is denoted by ***, **, * at the 1%, 5%, and 10% levels, respectively.

		(a) First Lag		(b) Second Lag		(c) Third Lag	
	Rolling Months	Less Vulnerable	More Vulnerable	Less Vulnerable	More Vulnerable	Less Vulnerable	More Vulnerable
Average	42	-11.958	-5.972	-3.713	4.913*	-2.521	-0.673
Principal Component	42	-11.342	-5.613	-2.601	5.880**	-2.240	-0.564
Average	54	-13.640	-0.343	-10.538	1.787**	-2.329	-3.080
Principal Component	54	-12.686	-0.369	-7.967	2.427**	-1.496	-3.006
Countries		7	7	7	7	7	7

Table 7: Model Parameters

This table presents model parameters selected for the real-options model.

Parameter	**Value**
Planning horizon: T	50
Annual debt issuance: X	1
Premium multiplier: m	1.46%
Initial flood probability: $p(0)$	1%
Construction duration: L	10
Construction cost multiplier: c	1% to 7%
Bottleneck probability: p_b	41%
Upkeep cost percentage	1%
Risk-free rate range	2% to 6%
Damages debt range	1% to 15%

Table 8: News, sovereign CDS returns and exposure to other climate risks

This table reports the regressions that relate news on international climate summits to sovereign CDS returns at 1-, 5-, and 10-year maturities for countries at risk from extreme sea level (ESL) hazards. I control for changes in the 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. I also include the average temperature anomaly, precipitation, and drought experienced by a sovereign. The coefficient in the first row represents an interaction between a news index on attention to climate summits and an indicator *Vulnerable* representing vulnerability to ESL hazard. *Vulnerable* is equal to one when referring to the group of sovereigns in the fourth quartile of Table 4, and zero when referring 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 ***, **, *.

	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr
Vulnerable × International Summits	3.268	3.914*	4.418***
	(3.465)	(1.966)	(1.619)
International Summits	4.705	1.546	0.528
	(3.305)	(1.538)	(1.403)
Carbon Intensity	10.914	3.785	3.476
	(12.027)	(3.929)	(3.410)
International Summits × Carbon Intensity	-23.600	0.463	1.045
	(30.010)	(11.444)	(10.599)
Temperature	0.247	0.053	0.028
	(0.269)	(0.094)	(0.083)
International Summits × Temperature	-0.975*	-0.385	-0.129
	(0.569)	(0.243)	(0.206)
Exposure	-0.084	-0.109	-0.087
	(0.280)	(0.122)	(0.099)
Readiness	-0.176*	-0.097**	-0.044
	(0.091)	(0.042)	(0.027)
Infrastructure	-0.158*	-0.067	-0.070
	(0.086)	(0.047)	(0.043)
Precipitation	-0.217	0.018	0.064
	(0.196)	(0.116)	(0.117)
Drought	0.451*	0.073	0.079
	(0.235)	(0.123)	(0.091)
Controls	Yes	Yes	Yes
SovereignxMonth	Yes	Yes	Yes
Rating	Yes	Yes	Yes
Adj R Squared	0.309	0.384	0.358
Observations	4972	4979	4971

Table 9: Sovereigns more vulnerable to extreme sea level rise hazard according to various data sources

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 vulnerable 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). Panel B 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 JAXA is obtained from Kulp and Strauss (2019).

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. JAXA		
Vietnam	Denmark	Japan
Belgium	China	United Kingdom
Germany	Indonesia	Ireland
Finland	Norway	France
Thailand	Latvia	

Table 10: Impact of news on sovereign CDS returns conditional on vulnerability to extreme sea level hazard, according to other data

This table reports the regressions that relate news on international climate summits to 1-, 5-, and 10-year sovereign CDS returns for countries at risk from extreme sea level (ESL) hazards according to a different elevation model. The International Summits index from Faccini et al. (2023) measures media attention to climate summits and is interacted with *Vulnerable* to produce the first-row coefficients, indicating the differential impact on CDS spreads between vulnerable groups. The *Vulnerable* sample of sovereigns—14 in total denoted in panel (b) of Table 9—consists of the more vulnerable sovereigns according to elevation data from the Japan Aerospace Exploration Agency (JAXA). Data for ESL hazard exposure is obtained from Kulp and Strauss (2019). 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 ***, **, *.

	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
Vulnerable × International Summits	3.643	3.416*	3.917**	3.315	3.326	3.901**
	(3.153)	(1.948)	(1.678)	(3.319)	(2.067)	(1.748)
International Summits	1.806	0.856	0.911	6.001*	1.953	1.298
	(1.774)	(0.948)	(0.911)	(3.514)	(1.624)	(1.540)
Carbon Intensity				2.100	2.466	3.121
				(11.583)	(3.887)	(3.504)
International Summits × Carbon Intensity				0.765	5.081	0.981
				(26.670)	(10.753)	(10.412)
Temperature				0.223	0.034	0.047
				(0.273)	(0.103)	(0.090)
International Summits × Temperature				-1.001	-0.271	-0.105
				(0.617)	(0.260)	(0.229)
SPX Returns	-1.481***	-0.840***	-0.666***	-1.473***	-0.838***	-0.662***
	(0.181)	(0.076)	(0.063)	(0.182)	(0.077)	(0.064)
MSCI Local Returns	-1.206***	-0.528***	-0.390***	-1.208***	-0.529***	-0.390***
	(0.138)	(0.054)	(0.044)	(0.138)	(0.054)	(0.044)
MSCI Vol	0.024***	0.014***	0.010***	0.024***	0.014***	0.010***
	(0.007)	(0.004)	(0.003)	(0.007)	(0.004)	(0.003)
FTSE Bond Index	-1.044***	-0.339***	-0.290***	-1.055***	-0.344***	-0.296***
	(0.301)	(0.117)	(0.101)	(0.297)	(0.117)	(0.100)
Exchange Rate Dollar	0.186	0.276*	0.182	0.196	0.278*	0.182
	(0.244)	(0.152)	(0.116)	(0.248)	(0.154)	(0.118)
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	0.064*	0.012	-0.009	0.062*	0.012	-0.009
	(0.036)	(0.012)	(0.010)	(0.036)	(0.012)	(0.010)
VIX	-0.026	-0.011	-0.012**	-0.026	-0.012	-0.012**
	(0.024)	(0.009)	(0.006)	(0.024)	(0.009)	(0.006)
SovereignxMonth	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adj R Squared	0.302	0.370	0.338	0.302	0.371	0.339
Observations	5085	5091	5090	5085	5091	5090

Table 11: Sensitivity of CDS returns to news for sovereigns protected against extreme sea level hazard

This table reports the regressions that relates news on 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. $Internationalsummits$ is a time-series index developed in Faccini et al. (2023) that captures global media attention to international climate summits across Reuters newswires. Changes in yearly carbon intensity is obtained from Climate Watch and abnormal temperatures from Berkeley Earth. 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 ***, **, *.

	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
International Summits	5.346	3.281	1.020	5.853	3.311	0.862
	(9.707)	(3.427)	(3.252)	(9.681)	(3.310)	(3.301)
Carbon Intensity				5.924	-1.397	1.532
				(15.703)	(6.365)	(4.716)
Temperature				-0.598**	0.030	0.062
				(0.157)	(0.205)	(0.097)
SPX Returns	-1.643*	-0.617*	-0.562**	-1.686**	-0.615**	-0.558**
	(0.651)	(0.240)	(0.174)	(0.644)	(0.235)	(0.171)
MSCI Local Returns	-1.490***	-0.595**	-0.427**	-1.489***	-0.595**	-0.427**
	(0.314)	(0.188)	(0.156)	(0.313)	(0.188)	(0.157)
MSCI Vol	0.027	0.009	0.006	0.026	0.009	0.007
	(0.032)	(0.009)	(0.003)	(0.031)	(0.009)	(0.003)
FTSE Bond Index	-0.297	-0.162	-0.276	-0.297	-0.159	-0.281
	(1.077)	(0.278)	(0.237)	(1.082)	(0.265)	(0.232)
Exchange Rate Dollar	0.031	0.502***	0.505**	0.037	0.504***	0.499*
	(0.740)	(0.100)	(0.195)	(0.741)	(0.093)	(0.195)
Intl Reserves	-0.038**	-0.029	-0.056***	-0.035**	-0.028	-0.057***
	(0.014)	(0.020)	(0.007)	(0.012)	(0.020)	(0.007)
5 Yr Treasury	0.027	-0.013	-0.051	0.028	-0.014	-0.051
	(0.096)	(0.033)	(0.034)	(0.096)	(0.033)	(0.034)
VIX	-0.040	-0.004	-0.023	-0.046	-0.004	-0.022
	(0.062)	(0.012)	(0.012)	(0.060)	(0.011)	(0.011)
SovereignxMonth	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adj R Squared	0.257	0.291	0.291	0.258	0.291	0.291
Observations	692	693	692	692	693	692

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

This table reports the regressions that relates news on international climate 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 Faccini et al. (2023) that captures global media attention to international climate summits across Reuters newswires. Changes in yearly carbon intensity is obtained from Climate Watch and abnormal temperatures from Berkeley Earth. 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 ***, **, *.

	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
International Summits	-7.129	-1.705	0.004	-6.785	-1.409	0.130
	(-0.78)	(-1.92)	(0.00)	(-0.67)	(-1.77)	(0.16)
Carbon Intensity				-10.366	-3.639	-1.839
				(-0.65)	(-0.74)	(-0.67)
Temperature				0.255	-0.087	-0.030
				(0.46)	(-1.20)	(-0.38)
SPX Returns	-1.234	-0.521**	-0.376*	-1.216	-0.527**	-0.378*
	(-1.86)	(-3.43)	(-2.47)	(-1.79)	(-3.58)	(-2.50)
MSCI Local Returns	-1.240**	-0.318	-0.235	-1.244**	-0.318	-0.235
	(-3.00)	(-1.53)	(-1.24)	(-3.00)	(-1.54)	(-1.24)
Debt to GDP	-0.206**	-0.085***	-0.057***	-0.203**	-0.091***	-0.060***
	(-3.86)	(-5.64)	(-6.48)	(-3.81)	(-6.88)	(-7.91)
MSCI Vol	0.022	0.002	-0.002	0.022	0.002	-0.002
	(0.82)	(0.25)	(-0.40)	(0.82)	(0.24)	(-0.42)
FTSE Bond Index	-1.753*	-0.551**	-0.429**	-1.739*	-0.538*	-0.422**
	(-2.52)	(-2.65)	(-3.43)	(-2.49)	(-2.47)	(-3.19)
Exchange Rate $	-0.136	0.303***	0.340***	-0.133	0.316***	0.346***
	(-0.10)	(4.88)	(4.05)	(-0.10)	(6.21)	(4.05)
Intl Reserves	0.103**	-0.013	-0.023	0.103**	-0.012	-0.023
	(2.72)	(-0.64)	(-1.18)	(2.62)	(-0.62)	(-1.19)
5 Yr Treasury	-0.079	-0.005	-0.024	-0.082	-0.006	-0.025
	(-1.01)	(-0.26)	(-1.42)	(-1.03)	(-0.27)	(-1.44)
VIX	0.012	0.012	0.010	0.014	0.011	0.010
	(0.14)	(0.81)	(0.79)	(0.16)	(0.71)	(0.71)
SovereignxMonth	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adj R Squared	0.112	0.155	0.144	0.109	0.153	0.141
Observations	672	674	673	672	674	673

Table 13: Impact of news on sovereign CDS returns conditional on vulnerability to extreme sea level hazard, controlling for liquidity

This table reports the regressions that relate news on international climate summits to 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 row reports the interaction term from interacting news index, $InternationalSummits$, with an indicator variable distinguishing countries more or less vulnerable to ESL hazard. *Vulnerable* is equal to one when referring to the group of sovereigns in the fourth quartile of Table 4, and zero when referring 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 ***, **, *.

	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
Gamma	3.008**	0.043	0.449	3.016**	0.097	0.483
	(1.419)	(0.567)	(0.439)	(1.416)	(0.579)	(0.439)
Vulnerable × International Summits	1.534	3.431*	3.982**	1.763	3.604*	4.074**
	(3.282)	(1.889)	(1.540)	(3.302)	(1.949)	(1.594)
International Summits	1.402	0.408	0.351	5.134	1.884	0.870
	(1.757)	(0.944)	(0.850)	(3.201)	(1.515)	(1.380)
Carbon Intensity				8.686	2.702	2.364
				(12.008)	(3.951)	(3.470)
International Summits × Carbon Intensity				-14.976	3.731	4.442
				(28.784)	(11.365)	(10.368)
Temperature				0.270	0.071	0.042
				(0.270)	(0.096)	(0.083)
International Summits × Temperature				-0.988*	-0.415	-0.163
				(0.580)	(0.250)	(0.207)
SPX Returns	-1.593***	-0.840***	-0.676***	-1.581***	-0.837***	-0.673***
	(0.186)	(0.075)	(0.063)	(0.187)	(0.076)	(0.064)
MSCI Local Returns	-1.125***	-0.518***	-0.381***	-1.126***	-0.518***	-0.382***
	(0.150)	(0.065)	(0.049)	(0.150)	(0.065)	(0.049)
MSCI Vol	0.024***	0.012***	0.009***	0.024***	0.011***	0.009***
	(0.009)	(0.004)	(0.003)	(0.009)	(0.004)	(0.003)
FTSE Bond Index	-1.048***	-0.458***	-0.392***	-1.067***	-0.463***	-0.398***
	(0.321)	(0.115)	(0.100)	(0.317)	(0.115)	(0.100)
Exchange Rate Dollar	0.300	0.330**	0.212*	0.311	0.333**	0.212*
	(0.265)	(0.160)	(0.119)	(0.269)	(0.162)	(0.120)
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	0.093**	0.014	-0.006	0.092**	0.014	-0.006
	(0.036)	(0.011)	(0.010)	(0.036)	(0.012)	(0.010)
VIX	-0.023	-0.009	-0.011*	-0.022	-0.009	-0.011*
	(0.024)	(0.008)	(0.006)	(0.024)	(0.008)	(0.006)
SovereignxMonth	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adj R Squared	0.308	0.381	0.355	0.308	0.382	0.356
Observations	5088	5094	5086	5088	5094	5086

Table 14: Impact of Google Trends on sovereign CDS returns conditional on vulnerability to extreme sea level hazard

This table presents regression results linking 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 coefficients in the first row represents the interaction term between the indicator variables *Google Trends* and *Vulnerable*. *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 75th (panel a) or 90th (panel b) percentile and 0 otherwise. *Vulnerable* is equal to one when referring to the group of sovereigns in the fourth quartile of Table 4, and zero when referring to those in the first and second quartiles. ESL hazard 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. T statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, *.

	(a) 75th Percentile			(b) 90th Percentile		
	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
Google Trends × Vulnerable	2.403	0.964	1.018*	6.638**	2.160**	1.770**
	(1.37)	(1.15)	(1.92)	(2.54)	(2.25)	(2.52)
Google Trends	-0.619	0.367	0.086	-1.443	0.278	0.088
	(-0.67)	(1.04)	(0.34)	(-1.14)	(0.52)	(0.24)
Carbon Intensity	8.770	2.290	1.764	9.504	2.509	1.953
	(0.82)	(0.65)	(0.52)	(0.88)	(0.71)	(0.57)
International Summits × Carbon Intensity	-24.471	-3.119	-1.657	-26.279	-3.557	-2.070
	(-0.91)	(-0.28)	(-0.15)	(-0.97)	(-0.31)	(-0.18)
Temperature	0.227	-0.024	0.004	0.223	-0.030	0.001
	(0.91)	(-0.31)	(0.06)	(0.90)	(-0.38)	(0.01)
International Summits × Temperature	0.016	0.068	0.100	0.015	0.082	0.106
	(0.04)	(0.33)	(0.56)	(0.03)	(0.39)	(0.59)
MSCI Local Returns	-0.789***	-0.362***	-0.259***	-0.787***	-0.360***	-0.258***
	(-5.75)	(-5.75)	(-5.56)	(-5.74)	(-5.72)	(-5.54)
Debt to GDP	-0.038	0.012	0.022	-0.031	0.011	0.022
	(-0.24)	(0.11)	(0.28)	(-0.19)	(0.10)	(0.28)
MSCI Vol	0.015	0.006*	0.006**	0.015	0.006*	0.006**
	(1.49)	(1.89)	(2.27)	(1.47)	(1.93)	(2.31)
Exchange Rate Dollar	0.394	0.325*	0.229	0.396	0.327*	0.231
	(1.23)	(1.81)	(1.65)	(1.24)	(1.81)	(1.65)
Intl Reserves	-0.000***	0.000***	0.000***	-0.000***	0.000***	0.000**
	(-2.97)	(9.22)	(2.97)	(-3.24)	(7.82)	(2.35)
Country	Yes	Yes	Yes	Yes	Yes	Yes
YearxMonth	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adj R Squared	0.364	0.469	0.451	0.364	0.470	0.451
Observations	4972	4978	4970	4972	4978	4970

Table 15: Panel vector autoregressions testing for sovereign CDS return predictability

This table reports the third order panel vector autoregressions investigating the relationship between the three month lagged values of the news index and monthly sovereign CDS returns for a 10-year maturity. The International Summits index from Faccini et al. (2023) measures media attention to climate summits and is interacted with *Vulnerable* to produce the coefficients in the first three rows, indicating the differential impact on CDS spreads between vulnerable groups. To calculate ΔESL, I begin with the 14 most exposed sovereigns to coastal flooding (fourth quartile, Table 4). ΔESL 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). Sovereigns are split into more- (1) and less-vulnerable (0) groups, represented by *Vulnerable*, based on whether a sovereign's trend coefficient is above or below the median across the 14 sovereigns. Splits are shown in Figure 3. The J-statistic is presented in the last row of the table. 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. The coefficients of sovereign CDS returns are multiplied by 100. Standard errors, in parentheses, are clustered by sovereign. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, *.

	Future Trend
	(1)
L.International Summits × Vulnerable	-5.018
	(-0.533)
L1.International Summits × Vulnerable	15.166***
	(2.997)
L3.International Summits × Vulnerable	3.612
	(1.013)
L.10 Yr CDS Growth	-0.318*
	(-1.736)
L2.10 Yr CDS Growth	0.017
	(0.962)
L3.10 Yr CDS Growth	0.052*
	(1.660)
SPX Returns	-0.446**
	(-2.024)
MSCI Local Returns	-0.519***
	(-5.410)
Debt to GDP	1.314
	(1.555)
MSCI Vol	0.016***
	(2.882)
FTSE Bond Index	0.099
	(0.314)
Carbon Intensity	-65.128**
	(-2.218)
Temperature	1.283***
	(2.802)
Exchange Rate Dollar	0.132
	(0.386)
Intl Reserves	0.000***
	(4.503)
5 Yr Treasury	0.032
	(0.920)
VIX	-0.011
	(-0.706)
N	1596
J	5.923

8 Figures

Figure 1: Exhibits from Climate Assessment Reports

Figure 1 presents two exhibits from the United Nations Intergovernmental Panel on Climate Change Assessment reports. The figure on the left is obtained from second page of the 4th assessment report published in 2007 and figure on the right is from the 5th assessment report published in 2014.

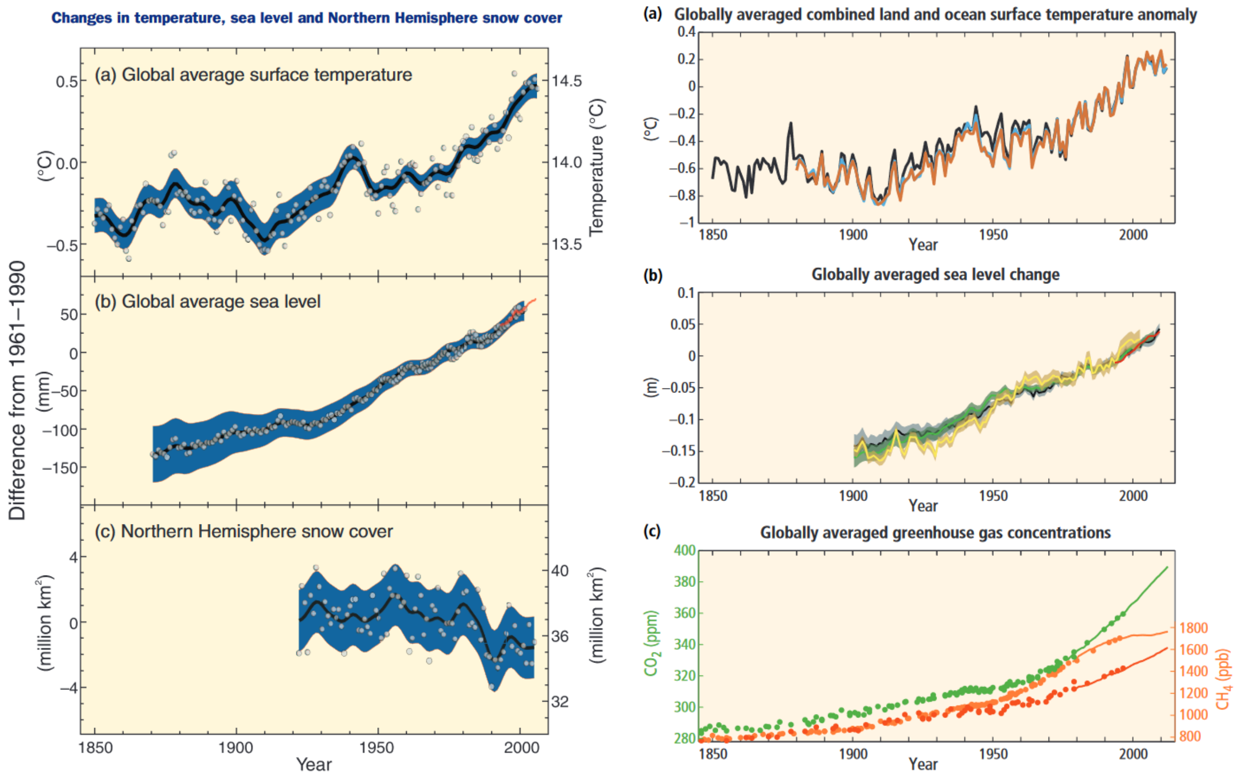


Figure 2: International Climate Summit News Index

Figure 2 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 summits by the sovereign credit market.

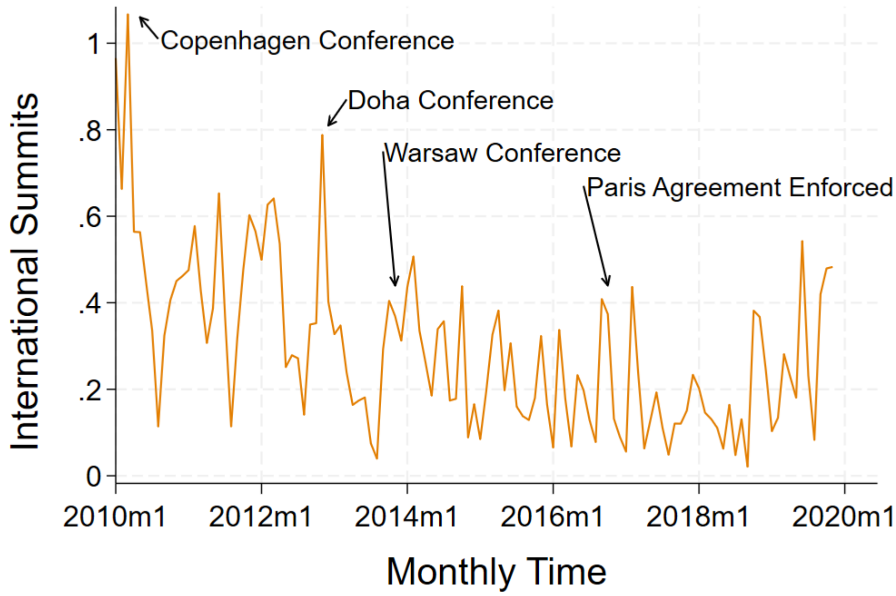


Figure 3: Changes in extreme sea level hazard using forecasted data

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 14 sovereigns more exposed to *ESL* hazard, i.e., the fourth quartile 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.

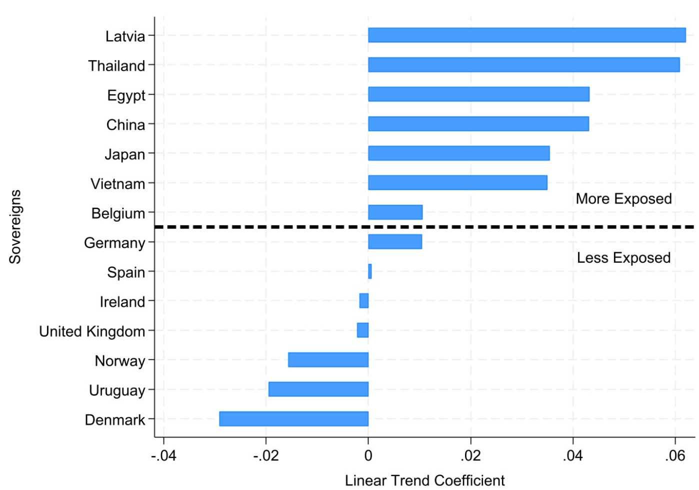


Figure 4: Comparative Statics for the Expected Present Value

This figure provides comparative statics for the expected present value of interest payments at various times to investment. The values represent the differentiations of the parameters: bottleneck probability, construction costs, damages, the premium attached to coastal flooding and SLR exposure, with increments of 0.01.

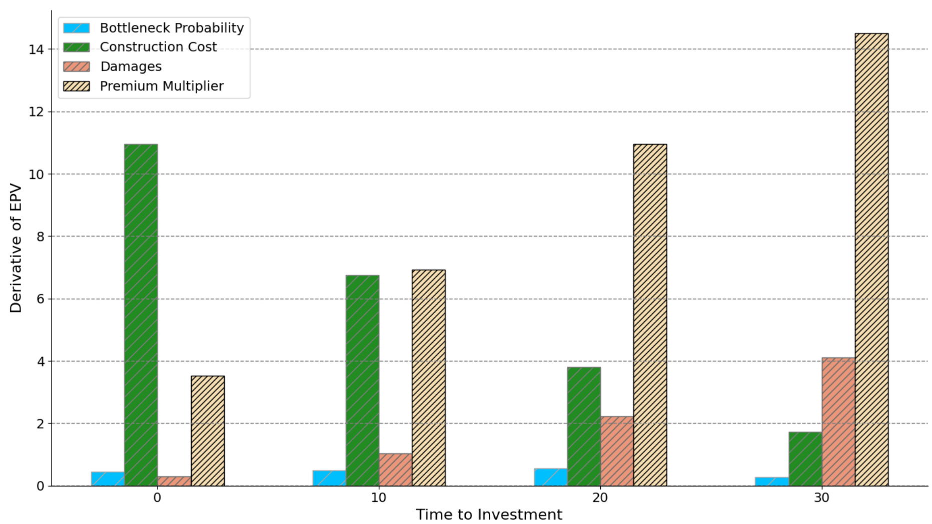


Figure 5: Example Path of Model

This figure illustrates a single decision-making outcome for a sovereign with a planning horizon of t(50) years. The sovereign issues debt at a rate, $r \times premium$ before the construction is finished and r after. The sovereign decides to begin construction at s with an plan that the construction will be completed in 10 years $L_{planned}$; however, there is a probability of a bottleneck occurring in a period (modeled as a Bernoulli random variable), extending the length of time required to complete the project to L_{actual}. The dash-dot gray line represents the exponential growth curve of flooding based on the projections of Taherkhani et al. (2020). Flood events are represented by the patterned rectangles which occur as a Poisson process, allowing more than one event to occur per period.

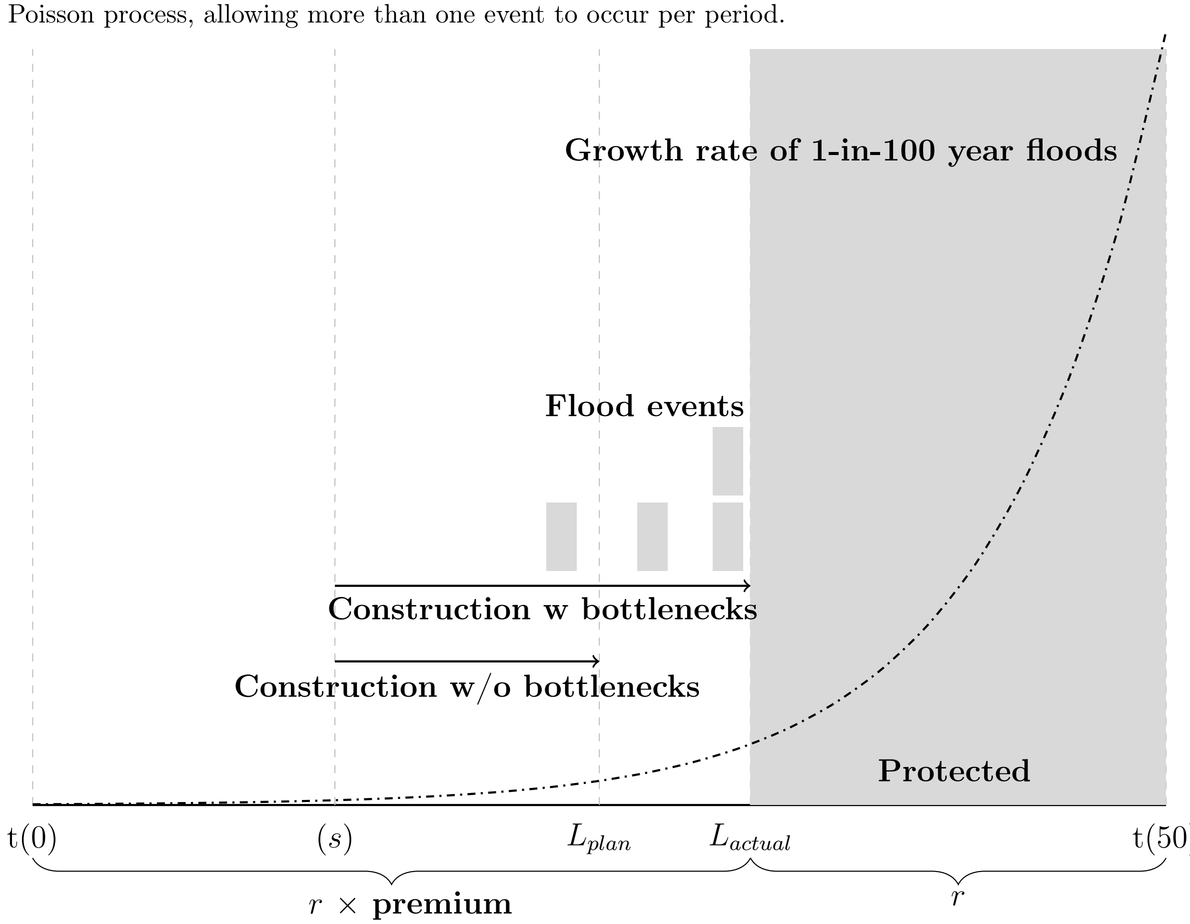
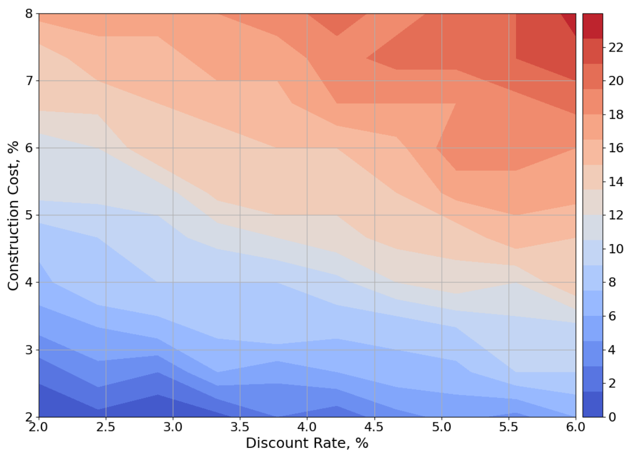


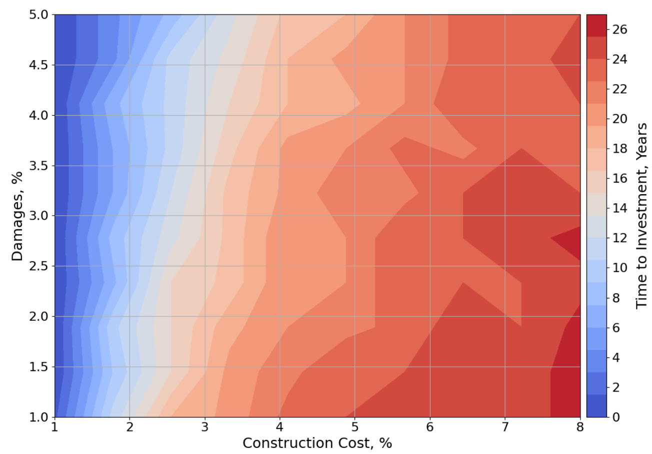
Figure 6: Sensitivity Analysis

This figure presents the sensitivity of the optimal time-to-investment while varying the parameters: construction cost and the discount rate in panel (a), construction costs and damages in panel (b), damages and the discount rate in panel (c), and the premium and the discount rate in panel (d).

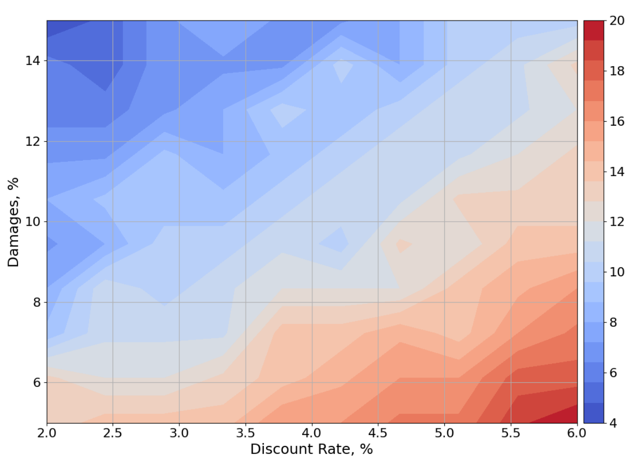
(a) Construction Costs



(b) Construction and Damages



(c) Damages



(d) Premium

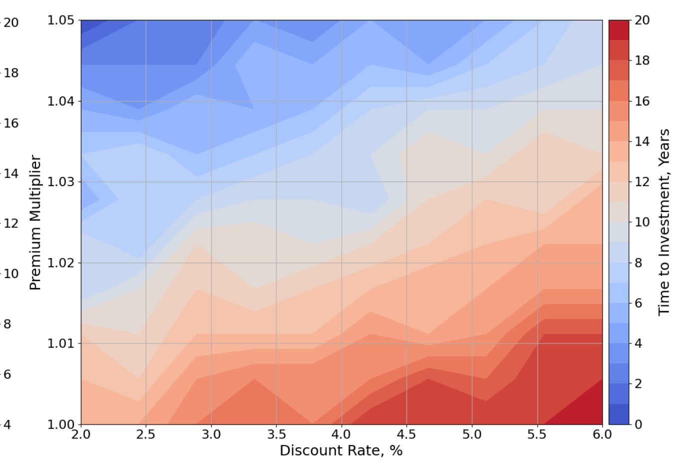
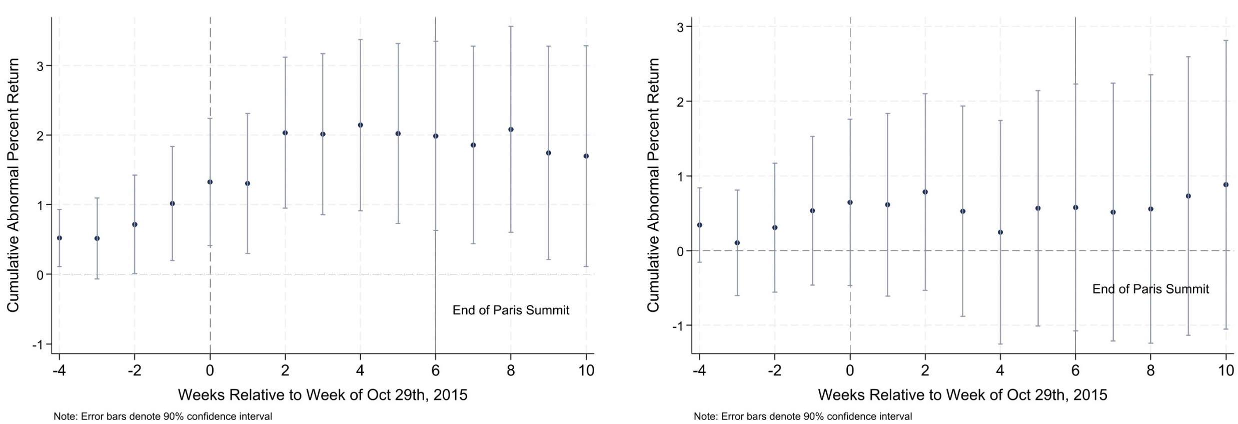


Figure 7: Cumulative abnormal returns for sovereigns vulnerable to extreme sea level hazard around the Paris Climate Summit

Figure 7 presents the cumulative abnormal returns (CAR) of the more vulnerable sovereigns to extreme sea level rise hazard in 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.

(a) More vulnerable sovereigns.

(b) Less vulnerable sovereigns.



9 Appendix A

9.0.1 Placebo Tests

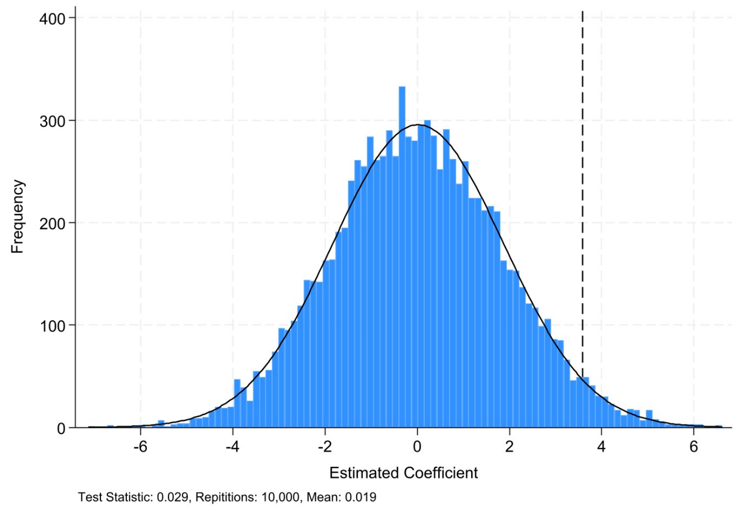
To rule out spurious correlations, I conduct placebo tests by randomly assigning sovereigns to different quartiles. Using this random allocation, I adjust the indicator variable, *Vulnerable*, according to the new quartile sort and conduct the main specification for either 5- and 10-year returns. I repeat this process 10,000 times and present the estimated coefficients in Figures 8 and 9 for 5- and 10-year returns, respectively. The figures present near-normal distributions of coefficients with the actual estimated coefficient as a vertical dashed line. The test statistic is calculated as the fraction of coefficients from the randomized regressions that exceed the main result. Overall, the distribution of values indicates that the sorting technique does not inherently produce spurious correlations between vulnerability and returns, validating the robustness of the main results.

9.1 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, γ, with:

Figure 8: 5 year



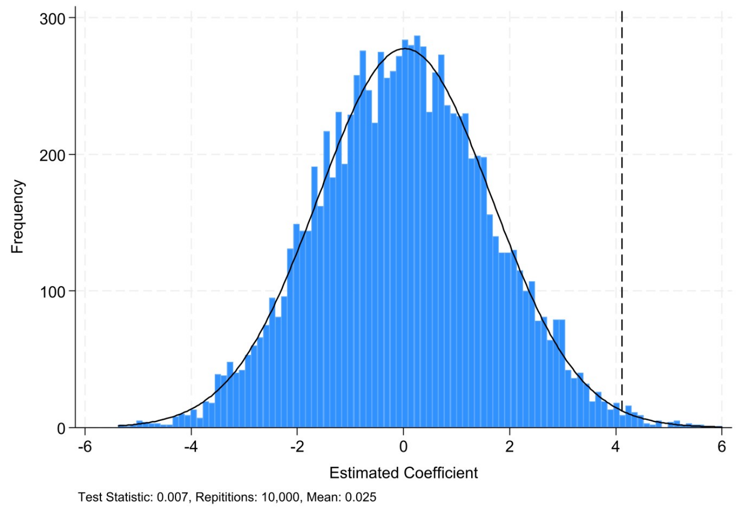
This figure presents the coefficients on the interaction term from the main specification for 5-year sovereign CDS returns when sovereigns are randomly assigned to vulnerability. Specifically, the 59 sovereigns are randomly assigned into vulnerability quartiles. Then, the indicator *Vulnerable* is set to one when referring to the group of sovereigns in the fourth quartile, and zero when referring to those in the first and second quartiles. This indicator is interacted with the $InternationalSummits$ index from Faccini et al. (2023) which measures media attention to climate summits. This process is conducted 10,000 times to produce the coefficients presented in this histogram. The actual coefficient estimate, 3.582, from the main specification is the vertical dashed line. The test statistic is calculated as the fraction of coefficients from randomized regressions that exceed 3.582.

$$\gamma = -\operatorname{Cov}\left(\Delta p_t, \Delta p_{t+1}\right), \tag{12}$$

where $\Delta p_t = p_t - p_{t-1}$ is the price change from time $t-1$ to t. γ'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 13 presents the results of the regressions including γ 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

Figure 9: 10 year



This figure presents the coefficients on the interaction term from the main specification for 10-year sovereign CDS returns when sovereigns are randomly assigned to vulnerability. Specifically, the 59 sovereigns are randomly assigned into vulnerability quartiles. Then, the indicator *Vulnerable* is set to one when referring to the group of sovereigns in the fourth quartile, and zero when referring to those in the first and second quartiles. This indicator is interacted with the $International Summits$ index from Faccini et al. (2023) which measures media attention to climate summits. This process is conducted 10,000 times to produce the coefficients presented in this histogram. The actual coefficient estimate, 4.120, from the main specification is the vertical dashed line. The test statistic is calculated as the fraction of coefficients from randomized regressions that exceed 4.120.

contracts showing the greatest liquidity. The statistical significance of γ 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.

9.2 Alternative Attention Index

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).[26] 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.[27] 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 either above the 75th percentile or 90th percentile and 0 otherwise. This results in a variable which represents particularly high periods of attention in a country towards international summits.

Following the primary estimation approach outlined in specification 6, I use an interaction term between *Vulnerable* and *Google Trends* to analyze the relationship between local attention and returns within each exposure group. The distinction here is that the interaction involves two indicator variables, rather than a continuous variable by a categorical variable.

The first row of Table 14 presents the estimated betas of the interactive term—the difference between high levels of country-specific attention to international summits and CDS returns, conditional on exposure *ESL* hazard. In panel (a), I find that only the 10-year tenor is significant when setting the threshold at the 75th percentile for *Google Trends*. When applying a higher threshold in panel (b), all three tenors turn significant. While the coefficient for the 1-year spread has a large magnitude, I note that this effect size is due to the greater volatility of shorter term spreads. Nonetheless, the results suggest that the term structure may flatten with more local news and attention. This interpretation is in line with the evidence from Augustin (2018) that finds that the term structure inverts when domestic factors dominate.

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

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

[27] 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.

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 sovereigns vulnerable to coastal flooding.

9.3 Panel Vector Autoregressions

I estimate a panel vector autoregression estimated using generalized method of moments. The lagged interacted *Attention* index and $Vulnerable$ indicator is considered the endogenous variables of interest, while the control variables used in regression 6 are exogenous. 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 third-order panel VAR model, estimated with the second through fifth lags of the untransformed variables as instruments, is found to produce an insignificant J statistic.[28] I apply this structural regression to the *ESL*- and ΔESL-exposed groups with a Helmert transformation to remove sovereign-specific fixed effects.

The results for the PVAR regression for the ΔESL-exposed sovereigns are presented in Table 15, which illustrates that the sovereign CDS market underreacts 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 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.

In sum, the observed evidence supports a behavioral inattention story rather than one of rational inattention. Investors overlook long-term climate and demographic information, gradually integrating subsets of publicly available information. If investors are rationally

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

inattentive, then magnitudes across the entire sample would likely be smaller, implying weak predictability (Sims (2003); Van Nieuwerburgh and Veldkamp (2010)).

9.4 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 ΔESL 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. In Table 9, I include a DEM model developed by the Japan Aerospace Exploration Agency (JAXA) in 2016. The JAXA model uses 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 9.

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 10, 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.

9.5 Actual Trends in Exposure

Here, I calculate the observed trends in exposure to highlight differences in expected versus realized trends in coastal flooding vulnerability. The observed ΔESL 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.[29] 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 regress the yearly percentage exposed ($SLRE$) for each sovereign s on a linear time trend λ for the years 2000 through 2010. Figure 11 shows the split of countries based on the estimated

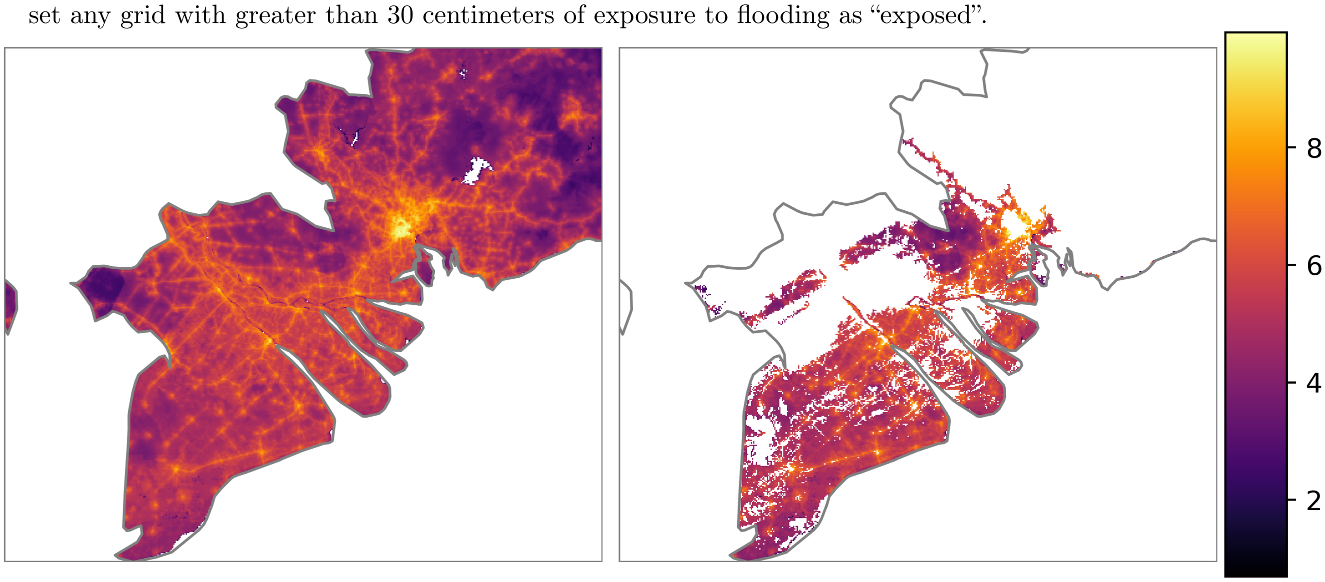
[29] Landscan, for example, changes its methodology every year, making it unsuitable for time series applications.

λ 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 10. This figure indicates a high population density around Ho Chi Minh City. The right panel of Figure 10 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.

Figure 10: Population of Ho Chi Minh City: total (Left) and vulnerable to extreme sea level hazard (Right)

Figure 10 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".



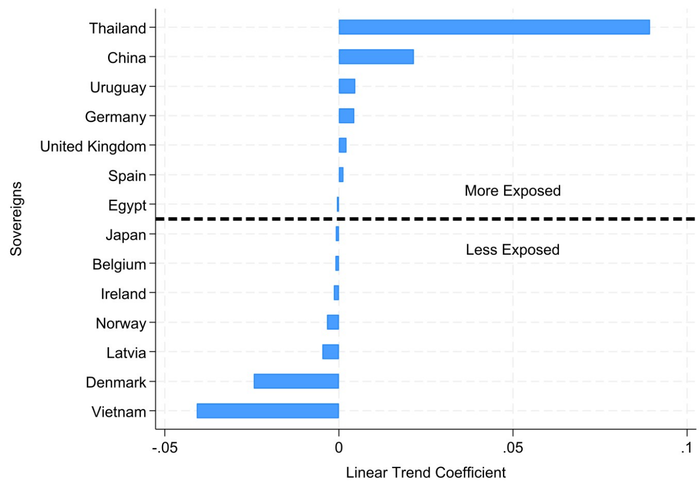
10 Appendix B

10.1 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

Figure 11: Changes in extreme sea level hazard using observed data

Figure 11 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 14 sovereigns more exposed to *ESL* hazard, i.e., the fourth quartile of vulnerable sovereigns as described in Table 4. 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 separating the estimated coefficients by their median value.



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, the details of which are described in the next section. 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, λ, which evolves stochastically and is time varying. This model assumes that the time of default, τ, 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:

$$SCDS_t(M) \approx \lambda_t(1 - R^Q), \tag{13}$$

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, λ. After estimating the risk premiums for each sovereign, more thoroughly discussed in Section 10.2, I winsorize the estimated risk premium returns at the 1.5%. I then conduct a similar style of panel regressions as outlined in equation 6.

Table 16 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 ΔESL hazards contemporaneously with news.

The regression results for 10-year risk premium returns for ΔESL-exposed sovereigns is found in Table 17. 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.

10.2 Sovereign decomposition model

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, λ_t, is described as the first jump of a Poisson process following the stochastic differential equation,

$$d \ln \lambda_t = \kappa^Q \left(\theta^Q - \ln \lambda_t \right) dt + \sigma_\lambda dB_t^Q, \tag{14}$$

where κ, θ, and σ 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,

$$SCDS_t(M) = \frac{2\left(1 - R^Q\right)\int_t^{t+M} E_t^Q\left[\lambda_u e^{-\int_t^u (r_s+\lambda_s)ds}\right]du}{\sum_{j=1}^{2M}\left[E_t^Q e^{-\int_t^{t+j/2}(r_s+\lambda_s)ds}\right]} \tag{15}$$

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 λ_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,

$$SCDS_t^Q(M) = \frac{2\left(1 - R^Q\right)\int_t^{t+M} D(t,u)E_t^Q\left[\lambda e^{-\int_t^u \lambda_s ds}\right]du}{\sum_{j=1}^{2M} D(t,t+j/2)E_t^Q\left[e^{-\int_t^{t+j/2}\lambda_s ds}\right]}. \tag{16}$$

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,

$$d\ln\lambda_t = \kappa^P\left(\theta^P - \ln\lambda_t\right)dt + \sigma_\lambda dB_t^P, \tag{17}$$

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

$$\eta_t = \delta_0 + \delta_1 \ln\lambda_t. \tag{18}$$

The parameters that determine the price of risk, δ_0 and δ_1, satisfy $\kappa^Q = \kappa^P + \delta_1\sigma_\lambda$ and $\kappa^Q\theta^Q = \kappa^P\theta^P - \delta_0\sigma_\lambda$. If δ_0 and δ_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,

$$SCDS_t^P(M) = \frac{2\left(1 - R^Q\right) \int_t^{t+M} D(t,u) E_t^P \left[\lambda e^{-\int_t^u \lambda_s ds}\right] du}{\sum_{j=1}^{2M} D(t, t+j/2) E_t^P \left[e^{-\int_t^{t+j/2} \lambda_s ds}\right]} \tag{19}$$

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 κ^Q, θ^Q and σ to recover λ 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,

$$\begin{aligned} f^P(\Theta, \lambda) =& f^P\left(\epsilon_{1y} \mid \sigma_\epsilon(1)\right) \times f^P\left(\epsilon_{10y} \mid \sigma_\epsilon(10)\right) \times f^P\left(\ln \lambda \mid \kappa^P, \kappa^P \theta^P, \sigma\right) \\ & \times \left|\partial SCDS^Q\left(\lambda \mid \kappa^Q, \kappa^Q \theta^Q, \sigma\right) / \partial \lambda\right|^{-1}, \end{aligned} \tag{20}$$

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 Δt being equal to 1/12 due to the monthly frequency of the data.

Table 16: Marginal effects of news on sovereign CDS premiums conditional on exposure to extreme sea level hazards

This table reports the regressions that relate news on international climate summits to 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 ***, **, *

	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
More Exposed × International Summits	3.264	3.273**	3.211**	4.065	3.459**	3.285**
	(0.70)	(2.18)	(2.66)	(0.84)	(2.25)	(2.53)
International Summits	-0.225	-0.097	0.680	10.977**	1.473	0.701
	(-0.10)	(-0.15)	(1.37)	(2.54)	(1.37)	(0.79)
Carbon Intensity				-8.170	-1.287	-1.575
				(-0.47)	(-0.31)	(-0.50)
International Summits × Carbon Intensity				-0.098	6.732	11.208
				(-0.00)	(0.62)	(1.33)
Temperature				0.991***	0.015	-0.045
				(2.82)	(0.18)	(-0.60)
International Summits × Temperature				-2.929***	-0.423*	-0.024
				(-3.36)	(-1.96)	(-0.11)
S&P Returns	-1.514***	-0.768***	-0.617***	-1.483***	-0.770***	-0.620***
	(-6.35)	(-11.81)	(-9.73)	(-6.23)	(-11.73)	(-9.75)
MSCI Local Returns	-1.100***	-0.385***	-0.301***	-1.104***	-0.385***	-0.300***
	(-7.07)	(-7.40)	(-7.35)	(-7.07)	(-7.38)	(-7.34)
Debt to GDP	-0.026	-0.025	-0.013	-0.020	-0.022	-0.007
	(-0.17)	(-0.36)	(-0.25)	(-0.13)	(-0.28)	(-0.12)
MSCI Vol	0.027**	0.008**	0.004	0.026**	0.008**	0.004
	(2.56)	(2.28)	(1.28)	(2.51)	(2.26)	(1.27)
FTSE Bond Index	-1.283***	-0.501***	-0.326***	-1.326***	-0.497***	-0.323***
	(-3.23)	(-5.29)	(-4.08)	(-3.35)	(-5.13)	(-4.02)
Exchange Rate $	0.158	0.239*	0.186*	0.180	0.241*	0.185*
	(0.54)	(1.73)	(1.85)	(0.60)	(1.74)	(1.84)
Intl Reserves	-0.000***	0.000***	0.000***	-0.000***	0.000***	0.000***
	(-49.98)	(45.36)	(22.10)	(-32.96)	(30.92)	(13.10)
5 Yr Treasury	0.119**	0.002	0.016*	0.113*	0.002	0.016*
	(2.07)	(0.17)	(1.97)	(1.95)	(0.13)	(1.96)
VIX	0.009	-0.003	-0.006	0.011	-0.004	-0.006
	(0.32)	(-0.39)	(-0.84)	(0.36)	(-0.47)	(-0.89)
SovereignxMonth	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adj R Squared	0.150	0.283	0.259	0.151	0.283	0.259
Observations	4928	4928	4928	4928	4928	4928

Table 17: Differential effect of news on sovereign CDS premiums by exposure to changes in extreme sea level hazard

This table reports regressions that relate news on international climate summits to 10-year sovereign CDS premium returns for countries vulnerable to changes in extreme sea level hazard. Premiums are obtained by decomposing 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 ΔESL, I begin with the 14 most exposed sovereigns to coastal flooding (fourth quartile, Table 4). ΔESL 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). Splits are shown in Figures 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. 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 1%, 5%, and 10% is denoted by ***, **, *.

	(1) 10 Yr	(2) 10 Yr
More Exposed × International Summits	-1.694	-1.151
	(2.245)	(2.155)
International Summits	4.206**	4.453*
	(1.788)	(2.269)
Carbon Intensity × International Summits		-16.317
		(15.683)
Temperature × International Summits		-0.129
		(0.442)
Carbon Intensity		8.143
		(5.107)
Temperature		0.034
		(0.198)
Debt to GDP	-0.238	-0.222
	(0.360)	(0.356)
MSCI Vol	0.005	0.004
	(0.006)	(0.006)
FTSE Bond Index	-0.192	-0.194
	(0.162)	(0.164)
S&P Returns	-0.703***	-0.700***
	(0.102)	(0.103)
MSCI Local Returns	-0.335***	-0.337***
	(0.068)	(0.068)
Exchange Rate $	-0.009	-0.008
	(0.106)	(0.108)
Intl Reserves	0.000***	0.000***
	(0.000)	(0.000)
5 Yr Treasury	0.014	0.014
	(0.014)	(0.014)
VIX	-0.034**	-0.034**
	(0.016)	(0.016)
SovereignxMonth	Yes	Yes
Rating	Yes	Yes
Adj R Squared	0.212	0.211
Observations	1539	1539