Surging Sovereign Spreads: The Impact of Coastal Flooding on Sovereign Risk

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Abstract

Coastal flooding, exacerbated by sea level rise, is a considerable economic threat to low-lying regions. I investigate whether investors account and insure for this hazard by exploiting the heterogeneity of country exposure to current and future coastal floods. Using sovereign credit default swap (CDS) spreads as premiums that incorporate information on credit quality and insurance demand, I document that severe coastal surge disasters increase the credit risk of affected countries across contract maturities. For a sample of 13 countries most vulnerable to short-term coastal flooding, I find a positive and significant relationship of sovereign risk to global and local attention toward physical and adaptation risks. In contrast, investors do not account for adverse future trends of flooding under climate model projections of sea levels, land subsidence, and population growth. Countries that have built protection against 1-in-100 year floods experience no increase in sovereign risk during periods of increased attention to adaptation risk. Additional tests demonstrate a positive and significant relationship between sovereign CDS trading and attention, explicitly revealing that investors purchase insurance against countries with existing flood exposure. The results suggest that sovereign risk will rise with the perception of coastal flooding, leading to increased financial pressures for exposed countries.

Keywords: Climate change, Credit default swaps, Sovereign risk, Investor attention, Sea level rise.

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

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Coastal flooding disasters have dire consequences to human life and sovereign economies, an example being the 2011 floods in Thailand, which caused the deaths of over 800 individuals and economic losses of $40 billion (Bank, 2012). Exacerbating the damages of *future* coastal surge events is the rise in global mean sea levels which, under Representative Concentration Pathway (RCP) 8.5, are expected to rise four feet by 2100 (Wuebbles et al., 2017). Further compounding the impending effects of climate change is the trend of populations projected to live in low elevation coastal zones that will increase from 625 million in 2000 to 1.4 billion in 2060 (Neumann et al., 2015). Finally, subsiding land will aggravate the negative effects of sea level rise. On average, these three factors should increase the severity and frequency of disastrous coastal surge events experienced by coastal sovereigns; however, there is substantial heterogeneity across regions in their current and future exposure.

Considering populations as a measure of economic activity, sovereign vulnerability to coastal flooding can be assessed as a function of two components: *stock* and *trend* risk.[1] *Stock* exposure represents the current vulnerability of a sovereign's populous to shore flooding which has remained largely static in modern history. The driver of recent historical changes to *stock* exposure has primarily been the movement of people as climate change has begun increasing the rate of sea level rise (SLR) only in the last two decades (Pörtner et al., 2019). In contrast, *trend* risk is the future rate at which a sovereign will experience coastal population growth, land subsidence, and sea level rise.[2] These three risk factors compound on one another to exacerbate *stock* risk, intensifying future calamitous coastal disasters.

In this paper, I investigate whether investors account for *stock* and *trend* coastal flooding risk by purchasing sovereign insurance as protection against disastrous events. I focus on sovereign credit default swap (CDS) spreads as they are an efficient gauge of a country's credit health, are useful instruments to insure against risk, and are available over multiple time-horizons (Pan and Singleton (2008);Augustin and Tédongap (2016);Augustin (2018)). The primary identification strategy exploits geospatial data of populations vulnerable to current and future coastal flooding to measure the differential exposure of sovereigns. To further identify whether investors insure the two risks, I use a set of indices that capture investor attention to climate risks and provide considerable time-series variation. The assumption here is that investors will demand

[1]The use of population as a proxy for economic activity has been used in Dell et al. (2012). Populations are more useful in this setting as they are forecasted into the future under different RCPs which is not the case for nightlights (Henderson et al., 2012), for example.

[2]Subsidence occurs when the ground beneath structures sink, pulling the structure into the earth.

more insurance when they are particularly attentive to climate threats (Giglio et al., 2021). Specifically, investors who are fearful of deteriorating credit worthiness from natural disasters (Chang et al., 2021), may purchase insurance against default risk for countries most exposed. This, in turn, will increase the equilibrium price of sovereign CDS spreads, particularly for the longer-term tenors.

The paper is motivated by Rietz (1988), Barro (2006), and Weitzman (2012), who offer a theoretical framework to understand rare disasters, investor reactions, and asset prices. In Barro and Weitzman's models, investors are concerned with events that produce grievously low levels of consumption and incorporate this fear into their investment decisions. A disaster has low probability of occurring for any one period, yet when experienced, sharply shrinks consumption and output for an economy that can lead to default (Barro, 2006). Equivalently, calamitous coastal flooding events are infrequent but produce ruinous economic outcomes (Michaels et al., 2020). Weitzman goes on to theorize that investors who are fearful of fat-tailed catastrophic events will desire insurance that yields a positive payoff in this low consumption world. In this setting, coastal surges pose a systemic threat to particularly vulnerable countries. Sovereign insurance thus becomes more valuable and increases in price when investors are attentive to the current and future severity of coastal flooding and SLR.

Disaster asset-pricing models are reliant on the probability of experiencing sporadic events that I contextualize in terms of coastal flooding. Countries with greater exposure to current *stock* risk are prone to more severe coastal floods - what Weitzman calls "fat-tailed" countries. By comparison, *trend* risk represents a change in the probability of disasters as increasing SLR, land subsidence, and population trends would intensify floods. I look to Wachter (2013) and Gourio (2008) who extend Barro's model to account for this time-varying risk. In Weitzman's world, investors who are aware and fearful of these two hazards would purchase sovereign CDS insurance to hedge against potential flood threats.

To test these theoretical underpinnings, I empirically confirm that surge events are catastrophic to sovereign creditworthiness. This step is critical as investors will not worry about coastal flooding if it has no perceived economic effects. I obtain the full breadth of the sovereign credit risk term structure by focusing on the 1-, 5-, and 10-year sovereign CDS tenors for 65 countries from January 2010 to November 2019. I gather historical event data on surges from international environmental disasters and conduct panel regressions to examine shocks to a country's credit risk. The results indicate that severe surge events, at the 90th percentile or greater, are associated with a sharp decrease in the creditworthiness of the country. The growth of the 1 year maturity rises more substantially than the 10-year maturity, in line with Augustin (2018) who finds a flattening of the term structure after a domestic shock.

While SLR is a slow moving phenomenon and surge events occur infrequently, the extent to which investors are attentive to this risk varies across time and is determinable (Hong et al. (2020); Giglio et al. (2021)). Attention and negative sentiment to climate threats act as state variables that proxy for the anxiety of investors who then buy insurance for protection. Explicitly, the increased global and local country attention is expected to be positively correlated with the investment decisions of investors. The global factors developed by (Faccini et al., 2021) are central to this study as they measure attention to physical and adaptation risk – two direct implications of rising seas. I additionally collect Google searches on the topic of "Sea Level rise' to measure the impact of country-specific attention shocks. If investors accurately account for risks, the equilibrium price of sovereign CDS spreads should only rise for countries most vulnerable to coastal flooding when there is greater concern.

To evaluate differential country exposure to coastal flooding risk, I calculate the percentage of a country's population that is vulnerable to 1-in-100 year coastal floods over the last two decades. After accounting for current SLR protection standards of countries, the sample is split into exposure quintiles where the fifth quintile is considered to be highly exposed and the remaining are deemed less exposed to *stock* SLR.[3] I measure *trend* risk in two ways. First, I estimate a historical time trend for each country using an AR(1) model for percentage of the population exposed in the last two decades. Second, I collect climate model data on future SLR risk as well as population estimates to generate a projected time trend in a similar fashion. I then equally split the fourth and fifth quintile of *stock* vulnerability to differentiate countries that are improving or worsening in their historical or future *trend* exposure.[4]

I next investigate *stock* exposure and its relationship to sovereign risk. The results indicate that a one standard deviation increase in the adaptation index corresponds to a 0.85% rise in the growth of longer term maturities (5- and 10- year sovereign CDS spreads) for highly exposed countries on average. In contrast, there is no significant relationship between the least vulnerable countries and sovereign risk across the term structure of CDS spreads. One interpretation is that exposed countries without any

[3] I crosscheck current protection standards from Lincke and Hinkel (2018) and set exposure to zero if a country is protected from a 1-in-100 year flooding event.

[4] I choose from the top two quintiles of *stock* risk as countries that are marginally exposed will not experience the adverse effects of SLR for many years.

protection against surges will have to invest in substantial infrastructure that need years to build, and in turn, investors react fearfully by purchasing insurance. Similarly, attention to global warming increases sovereign risk for the most exposed, but over both the short- and long-term. The least vulnerable countries only experience rising sovereign risk in the long-term. This is attributable to the economic threat that all countries will face in the future due to global warming. In all, the findings resound with the "disaster view" of Weitzman (2012) where investors hedge against a potential low consumption world in the event of a large-scale coastal flood.

Next, I conduct a parallel analysis with country-specific attention to "Sea Level Rise". I find that when local attention is two standard deviations above the mean, there is a contemporaneous increase of 1.69% in the growth of the 5- and 10-year sovereign CDS spreads for vulnerable countries, on average. The sample with little exposure to SLR, experiences no significant rise in sovereign risk over all maturities. These results once again support the discussed theoretical model of fear and attention driving investment in insurance. The economic significance of local attention is muted in comparison to global attention which suggests that while domestic shocks are important (Dieckmann and Plank (2012);Hilscher and Nosbusch (2010)), global determinants are more related to sovereign credit risk (Pan and Singleton, 2008).

To test if investors are accounting for *trend* risks, I employ the sample of improving and worsening countries based on historical and future SLR trends. In contrast to the prior tests, I focus solely on the growth of the 10-year CDS spread as *trend* SLR risk will only be relevant over the long horizon. The results indicate that neither historical nor future trends are accounted for. Explicitly, investors are not incorporating SLR trends when buying insurance against catastrophic surge events in the future. In the same vein, Murfin and Spiegel (2020) find that real-estate markets do not price the differential exposure of properties to rates of SLR. These findings reveal that investors are not integrating more complex information of *trend* vulnerability into their investment set and rather focus on *stock* exposure that is simpler to quantify.

I end the analysis with two robustness checks. First, I test if worldwide attention to adaptation and global warming is associated with increased sovereign risk for countries that have built protections against 1-in-100 year floods. The results suggest that there is no significant rise in risk for these countries, implying that investors account for current protection standards. In comparison, there is a more substantial, but non-significant, increase for the global warming index. An explanation for the finding is that countries are contending with broader climate risks such as rising temperatures.

Second, I provide evidence of increased sovereign CDS trading activity during raised attention to climate risks. The percentage growth of weekly trades and gross notional amounts of sovereign CDS is found to be positively associated with adaptation and global warming risks. The findings support evidence that investors hedge against sovereign risk using CDS contracts which is consistent with Augustin et al. (2016).

The evidence provided in this paper complements a growing empirical literature that investigates investor attention and response to climate change. Choi et al. (2020) find that investors react to local abnormal temperatures by selling carbon-intensive firms. Hong et al. (2019) present evidence of investor underreaction to country-level trends in droughts. Conversely, Schlenker and Taylor (2021) demonstrate that financial markets integrate climate warming projections. Giglio et al. (2021) find that transaction prices of properties in flood zones vary differentially as their attention index varies. Other studies illustrate the risk that sea level rise poses to various assets such as municipal bonds, ((Painter, 2020); (Goldsmith-Pinkham et al., 2021)), and house prices ((Baldauf et al., 2020); (Bernstein et al., 2019); Giglio et al. (2021);Nguyen et al. (2022)). In contrast, Murfin and Spiegel (2020) find no pricing effect for properties with greater exposure to rising rates of SLR.

I extend the literature to focus on global sovereign risk instead of other financial assets such as mortgages, municipal bonds, or sovereign bonds (Volz et al., 2020). Additionally, I find empirical evidence that supports both strands of the diverging literature on whether investors react to climate change risks. My results suggest that investors price simple, more quantifiable threats such as *stock* exposure to flooding rather than account for complex hazards such as the time-varying exacerbation of coastal flooding disasters. This study is also theoretically motivated by Weitzman (2012) and Barro (2006) in showing how investors purchase insurance against calamitous fat-tailed climate risks. Whereas Nguyen et al. (2022) considers SLR as a long-run risk in terms of the model of Bansal et al. (2017).

I also contribute to the contested literature on the economic drivers of sovereign credit risk. Many studies focus on the global drivers of sovereign CDS spreads ((Augustin and Tédongap, 2016), (Longstaff et al., 2011) and (Pan and Singleton, 2008)), while others highlight local factors ((Augustin et al., 2020); (Hilscher and Nosbusch, 2010)). My results lend credence to a combination of global and local factors that drive variation in sovereign risk, similar to the results of Dieckmann and Plank (2012) and Hilscher and Nosbusch (2010). However, I find evidence that global attention toward coastal floods has a more substantive relationship to sovereign credit risk.

1 Hypothesis Development

I use the class of asset-pricing models that view disasters as central to their mechanisms to steer my hypotheses. From the perspective of Weitzman (2012), a rare surge event can be considered a disaster with devastating repercussions to a *tail-exposed* investment conditional on consumption. In a sovereign risk setting, an investor's investments (e.g. sovereign bonds) in an exposed country would deteriorate when a tail event is realized. This position is aligned with the argument of Hilscher and Nosbusch (2010) who show a tight association between sovereign credit risk and country-specific macroeconomic fundamentals. Furthermore, Barro (2006) goes on to specifically tie default probability to the likelihood of a disaster occurring in any one period.

Sovereign CDS spreads are useful to study this phenomena as they are measures of a country's aggregate financial health and 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 to investigate both short- and long-term responses to climate shocks as they are standardized at 1-, 5-, and 10-year terms (Pan and Singleton, 2008). I expect that during particularly calamitous surge events, the credit quality of the affected country will weaken on average, leading to the first hypothesis.

Hypothesis $\mathbf{H_1}$: Growth in a sovereign's CDS spread increases when the country experiences a substantial surge event.

Weitzman (2012) suggests that if an investor is increasingly fearful of calamitous risks, the purchase of an independent investment that insures against a low-consumption world is valuable.[5] A *tail-hedged* investment would be expected to provide an investor with a positive payoff during a tail event. The larger the uncertainty about the future state of an economy and future consumption, the higher the value of this insurance. Fear, therefore, is the key to understanding the cost of hedging against particularly bad states of the world. I proxy fear of SLR risk using attention indices that focus on the physical and adaptation risk of climate change, akin to Giglio et al. (2021). Attention indices provide substantial time-series variation in comparison to the infrequent nature of destructive surge events. During periods of elevated attention toward climate change risks, investors should purchase insurance

[5] Weitzman (2012) and Giglio et al. (2021) discuss investment projects to mitigate climate change. Here, purchasing a sovereign CDS does not reduce the chance of future events which is an important departure from their models.

against countries that are especially exposed to SLR and surge risk. However, as discussed earlier, the likelihood of experiencing such an event is exceedingly low in the short-term which leads to my second hypothesis.

Hypothesis $\mathbf{H_2}$: There is a positive association between attention to climate risks and CDS spreads for countries with high *stock* exposure, particularly in the long-term.

Coastal flooding presents two separate sovereign risks: (1) a physical risk that represents the damages after a country experiences a disaster, and (2) an adaptation risk that constitutes either populations moving inland or a sizable investment to levees or dikes as protection. Circling back to hypothesis H_1, a shock to a sovereign would alert investors of potential future damages. In the same vein, general global attention to climate change could warn investors of other related threats such as SLR. Adaptation can also be costly, as one project – The Delta Works in the Netherlands – has taken four decades and \$13 billion to complete.[6] Therefore, attention to adaptation could also alarm investors to the costs and indirectly alert them of future damages by flooding events. Collectively, the "perception" of both physical and adaptation risk should cause investors to insure against vulnerable countries.

I also specify *stock* exposure in H_2 for two reasons. First, *stock* vulnerability is persistent in the cross-section of countries, which means that investors are not required to have knowledge of climate models to price this risk. Second, the sovereign CDS spreads for countries with this high ambient threat should be more sensitive to attention across the entire term structure. While there is a low likelihood of a tail event occurring in a given year, the chance of such an event is much larger over the long-term compared to another country with a lower *stock* exposure. In essence, these countries have fat-tailed probabilities of outlier catastrophic events, as described in Weitzman (2012). This implies that the most responsive sovereign CDS spreads should be the ones that insure investments over a longer horizon.

As a follow-up to hypothesis H_2, I investigate whether investors account for climate models and projections of future SLR. The literature is divided on whether or not markets price climatic trends as Bansal et al. (2017) argue that long-term temperature is priced in asset markets, while Hong et al. (2019) find an inefficient market. In a Weitzman (2012) view, investors would modify their tail-hedged investments as a consequence of heterogeneous sovereign exposure to *trend* risk. Of course, a country with little to no vulnerability to *stock* risk would remain safe to high *trend* risk

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

over the long-horizon. This minimum threshold of stock vulnerability implies that investors would have to accurately distinguish the SLR trends of countries that are currently exposed, which leads to my third hypothesis.

Hypothesis $\mathbf{H_3}$: Long-term sovereign CDS spreads should have a strong positive relationship with countries that have worsening sea level rise *trends* compared to countries with improving *trends*. This relation is apparent during periods of high investor attention and for countries that have heightened *stock* exposure.

Investors would not necessarily need to use recently developed climate models to differentiate the *trend* risk of countries. Instead, they may infer future risk based on the growth rate of population exposure in recent history as there is evidence that rates of SLR have gathered speed since 1993 (Hay et al., 2015). To test both cases, I calculate country exposure from both historical and future climate models. Collectively, the three hypotheses provide the basis for my empirical investigations.

2 Data and Methodology

I discuss the financial data used in Section 2.1 and harmful coastal surge events in Section 2.2. I describe in detail the methodology to calculate *stock* and *trend* exposure in sections 2.3 and 2.4. In Section 2.5, I explain the attention indices used in the analysis.

2.1 Financial Data

The sovereign CDS market is a useful setting to investigate the research question as the spread responds to changes in credit events rapidly (Longstaff et al., 2011). I acquire monthly sovereign CDS spread data from Datastream for 81 distinct countries. The spread data cover 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 growth rates for each country. I restrict the sample to the time periods of January 2010 through November 2019 as there is limited evidence of climate risk being priced before 2010.[7] I restrict the sample further to only include countries that have more than 80% of their observations as non-missing and different from zero.[8]

[7] Goldsmith-Pinkham et al. (2021) find little evidence of climate risk in the municipal bond market prior to 2010.

[8] The spreads of some countries are relatively stable and thus contain a large number of zero values.

These constraints reduce the sample size to 65 countries. The remaining regions used in this study are presented in Table 4. The sample consists of countries 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 empirical work as the basis for the economic and financial variables I gather at the monthly frequency from Datastream: the SP 500 excess returns, changes in the 5 year U.S. constant maturity Treasury yield, changes in the CBOE VIX volatility index, changes in the exchange rate relative to USD, and country excess stock market returns from MSCI. A few countries do not have their own MSCI index, therefore, I replace the regional MSCI index as their own. The European countries Cyprus, Latvia, Malta, Slovakia, and Armenia are replaced with 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 summary statistics are provided in Table 2.

2.2 Surge Events

To test hypothesis H_1, I collect data on surge events from the international disasters database (EM-DAT) (Shen and Hwang, 2019). The database is a commonly used source in economic and financial literature and documents natural disasters if they meet a certain threshold of harm: (1) ten or more deaths, (2) 100 or more individuals affected, (3) an emergency declaration, or (4) a call for international assistance. For instance, Karydas and Xepapadeas (2019) use the database to collect large-scale climate disaster events that reduced countries economic growth rates. Similarly, Eisensee and Strömberg (2007) use the data to investigate the nexus of mass media and U.S. government response to natural disasters in general. I follow this line of thinking and gather surge events that had material impacts on sovereigns.

To be thorough, I also gather information on flooding events from Dartmouth Flood Observatory which collects data from news and governmental sources (Brakenridge, Brakenridge). The records include the type of flood, where the flooding event occurred and the resulting damage in the number of individuals dead or displaced. The observatory also notes secondary countries that are affected by the flood which I include in my sample. I combine the Observatory data with EM-DAT and remove duplicate observations while giving precedence to the numbers reported in EM-DAT.

For my empirical work, I identify and select four specific disasters in the combined database that are associated with coastal surges: storm surge, high tides, tidal surge, and coastal floods. The number of flooding events documented is scarce as the event would have to be substantial for the country to be affected. The majority of storm surges will be rebuffed by coastal defenses and will cause no immediately visible damage. Only the disastrous surges will cause harm to people and the economy.

I match the data on these four disasters with my sample countries from 2010 on, which leaves 16 observations of surge events. I evaluate the severity of the surge events using the total number of people affected by the event in the EM-DAT database which encapsulates those that are injured and made home-less.[9] The severity metrics provided by EM-DAT are based on official sources from governments, non-profits, or insurance companies. While not directly equivalent, I assume that the individuals affected in the EM-DAT database correspond to the 'displaced' individuals in the Dartmouth Flood Observatory. The Observatory uses individuals displaced which are estimated from news sources and encapsulate the number of people made homeless or evacuated. These measures are then used to study particularly deadly surge catastrophes which may impact the economic welfare and creditworthiness of a region.

2.3 Stock Exposure

I analyse the *stock* exposure for the sample of 65 countries. To do so, I obtain the inundation extent data from the Global Tide and Surge Reanalysis (GTSR) data set created by Muis et al. (2016). Their methodology relies one two hydrodynamic climate models which simulate the rise in water during storm surges and tides. This approach produces probabilistic estimates of flooding extent which they validate using historical storm surges that occurred between 1980 and 2011. The output accounts for wind speed, atmospheric pressure, and elevation but disregards coastal protection already built. Their inundation dataset is in the form of a gridded raster file at a spatial resolution of 30" $\times$ 30" (1 $\times$ 1 km at the equator).

To calculate exposure, I select a realization of a 1-in-100 year flooding event that occurs globally to assess land at risk of coastal flooding and *stock* risk.[10] This return period of flooding is commonly used by climate scientists such as Hallegatte et al. (2013) and in turn applied in the economics literature (Painter, 2020). Furthermore, in asset-pricing models such as Barro (2006), disasters have to be sufficiently rare and

[9] Eisensee and Strömberg (2007), for example, uses both the total number killed and affected to measure disaster severity.

[10] In this case a 100 year event is a flood that has a 1% chance of occurring yearly.

devastating as to contract economic activity by more than 10% or more (Barro and Ursua, 2008). Economic exposure, however, is dependent on the depth of inundation since a splash of water on land will have no effect on people's lives. Hallegatte et al. (2013), for example, use a 40 cm surge event as the inundation threshold, assuming that anything below this minimum would have no impact on economic activity. I assume a minimum threshold of 30 cm that is in the higher range of the 'moderate risk' category developed by Rentschler and Salhab (2020).

To measure the economic activity in each 30" x 30" grid cell in the world, I use population headcounts at the same resolution. The estimated population is simple proxy for economic activity in a certain area and is commonly used in the economic literature. Population estimates at this granular level are a regularly used to proxy for economic activity in a location, for example, Dell et al. (2012) use gridded population to weight exposure to temperature and precipitation. In a similar fashion, I obtain yearly global population distribution data from LandScan (Bhaduri et al., 2002) for the years 2000 through to 2019. Their data describe the ambient population in a 24 hour period in a 1 km by 1 km grid cell for most of the world's countries.

Using geospatial software, I calculate the number of people in each country exposed to the GTSR dataset in the last two decades. The yearly exposure is obtained by overlaying the moderate risk inundation layer over the population grid. The population in the intersection at the two layers is aggregated up to the country-level and divided by the total population of the country in the year. Finally, the stock exposure is obtained by taking the average of the last two decades, which is presented in Table 4. I also obtain current SLR protection standards for the countries in the sample from Lincke and Hinkel (2018). Specifically, I set the exposure for the sovereigns Hong Kong, Israel, Italy, Qatar, Bahrain, and the Netherlands to zero.

This methodology produces rich heterogeneity in the sample. Table 4 shows that SLR exposure is highly skewed to the fifth quintile and drops off precipitously past the fourth quintile. As an example I highlight two countries, Vietnam and the Philippines, that have similar populations but large differences in exposure to *stock* SLR. Figures 1 and 2 illustrate the population in 2010 on the left-hand side and the exposed population on the right. The Philippines are mountainous and the population does not live near surge exposed coastal areas.[11] In contrast, a large part of the population of Vietnam lives near low lying coastal zones.

[11] This does not mean that the Philippines does not experience large surge events such as in 2013 when a large typhoon hit.

2.4 Trend Exposure

Research on the rates of sea level rise is rapidly developing. Prior to the 1990s global mean sea levels (GMSL) have risen steadily at a rate of 1–2 mm per year across the world (IPCC 6th Report). Recent work by Hay et al. (2015) shows this increase has quickened to a rate 3 mm per year since 1993. The future rate of SLR is highly uncertain; however, estimates point to a potential increase of 10–20 mm/year at the end of the century under the Representative Concentration Pathway 8.5. Furthermore, there is widespread heterogeneity in the rates of SLR across the globe due to ocean and geological processes. The increasing rate of SLR will intensify future flooding events across the globe.

I obtain future coastal flooding extent through the World Resources Institute under their Aqueduct Floods Methodology (Ward et al., 2020). Their approach produces future projections for coastal inundation for the years 2030, 2050, and 2080 at a resolution of 1 km x 1 km at the equator. Their projections are built on the Global Flood Risk with IMAGE Scenarios modeling framework that includes subsidence and forecasts under different RCPs. One of the key assumptions in the model is that coastal growth will continue into the future.

To remain consistent with the calculation of *stock* exposure, I select a 1-in-100 year coastal flooding incident to measure inundation extent for the years 2030, 2050, and 2080. I select the moderate global warming scenario of RCP 4.5 where the world stabilizes the release of CO_2 to 650 ppm compared to the current level of 400 ppm. Furthermore, the scenario is adjusted to include subsidence where 50 percent of the maximum damage occurs. Once again, I assume that water levels equal to or greater than 30 cm fully inundate an area of land.

To measure future population growth, I use data from Gao (2017). The data set contains gridded populations at a 1 km x 1 km resolution for every decade from 2000 to 2100. I download the decadal data under the Shared Socioeconomic Pathway Two, which was developed by the IPCC sixth assessment report. The pathway assumes that economic and social trends do not shift considerably from the current paradigm and is comparable to the RCP 4.5. I consider that SLR exposure, before 2030, can be represented by the flooding dataset developed by Muis et al. (2016). Therefore, I assume that exposure for the population data at years 2000, 2010, and 2020 can be estimated by overlaying the GTSR spatial flooding layer on each population layer – resulting in three point estimates of exposure for each country. For the years 2030 and beyond, I assume that each future flooding projection holds for the next decade.

In this case, the 2030 projection for flooding inundation under Ward et al. (2020) would hold for populations in 2030 and 2040. This methodology produces ten point estimates of country population exposure to SLR from 2000 to 2100. I calculate trends in SLR vulnerability using two separate methods: (1) by extrapolating out historical exposure based on data from the last two decades, and (2) estimating future trends with decadal point estimates. I use an AR(1) model, which includes a deterministic time trend for population exposure (SLRE) for a country c as follows:[12]

$$SLRE_{c,t} = a_c + \psi_c SLRE_{c,t-1} + \gamma_c t + \epsilon_{c,t}. \tag{1}$$

Here $\epsilon_{c,t}$ is the error term, a_c is a intercept, ψ_c is the autoregressive term, and γ_c is a country varying trend term. To calculate the trend term using the historical point estimates, SLRE is measured for each year from 2000 to 2019 and used as inputs into equation 1. Analogously, the trend term for future SLR is calculated from the ten point estimates from future population and flood exposure as outlined in this section. I denote the historical and future trends as *HTREND* and *FTREND*, respectively. The result of this analysis is presented in Table 9.

This methodology allows for the separation of historical and trend exposure. Prior literature typically uses an average GMSL for their analysis (Goldsmith-Pinkham et al. (2021);Bernstein et al. (2019);Baldauf et al. (2020)) or assume historical trends are indicative of future trends (Murfin and Spiegel, 2020). The heterogeneous risk should be reflected in sovereign CDS spreads if investors are aware of the costs of future coastal surge disasters and climate model projections. Leveraging this subtle variation, I investigate if investors accurately distinguish countries with either decreasing or increasing SLR trends.

2.5 Attention Indices

The sluggish rise in sea levels in the last two decades offers little time series variation for pricing. I instead investigate whether attention to climate risks have a role in sovereign CDS prices and trades. Attention indices have rich time-variation and are used as indirect methods of pricing climate risks. Heightened attention to climate risks are known to be drivers of prices in the bond (Painter, 2020), stock (Choi et al., 2020), and housing markets (Giglio et al., 2021). As SLR is a very specific concept, I leverage various global and local climate related attention indices that are related to

[12]This methodology is similar to Hong et al. (2019).

SLR. The theory we test is that news and attention to SLR affects investors, moving equilibrium prices of sovereign credit default swaps for highly affected countries.

To represent global attention to physical and adaptation risk, I adopt two news indices developed by Faccini et al. (2021). They uncover various factors by performing a textual analysis using Latent Dirichlet Allocation from a corpus of news sources. The 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. I selected two factors illustrated in Figure 3, international climate change summits and global warming as they represent worldwide rather than U.S.-centric news.

International summits represent events such as the Doha U.N. Climate Change Conference (November 2012) where governments and corporate representatives coordinate interventions to address a changing climate. Adaptation risks are often discussed during international summits. A recent example of this was at the COP26 World Leaders Summit on November 2nd, 2021, where Palau President Surangel Whipps Jr. called on industrialized nations to greatly increase their climate funding commitments for developing nations, including funding for climate adaptation. Another example occurred during the 2012 UN climate Change Conference in Doha where adaptation and mitigation were discussed as long-term threats.[13] Therefore, the index captures longer term adaptation risks as agreements discussed in summits may take years for nations to commit to. The global warming index considers news that warn readers about the risk of elevated green house gas emissions as well as the need to reduce them. One of the main events represented is a publication by the World Meteorological Organization (November, 2015) announcing that it was the hottest year on record. The factor represents the physical risks of global warming in the long-run.

Faccini et al. (2021) does not differentiate from positive or negative news for the factors. Rather, similar to Engle et al. (2020), the authors expect that these factors are likely to arise when there is a cause for concern. An increase in the value of both factors would indicate an adverse effect for an economy. One caveat is that these factors capture media attention explicitly rather than directly representing investor attention (Da et al., 2011). An increase in the intensity of climate news does not necessarily mean that investors will read the articles. Nonetheless, there is strong evidence that levels of news coverage is a suitable proxy for the level of attention investors pay to climate change (Ardia et al., 2020).

[13]From the Doha climate gateway, "Doha amendment to the Kyoto Protocol".

I explore another avenue of attention by using local, country-specific attention to SLR risk. I capture local attention to SLR by downloading monthly Google Search Volume Indices (SVI) for “Sea Level Rise” in 36 countries from 2004 to 2019. The assumption, similar to (Choi et al., 2020), is that country-specific internet searches for SLR are a proxy for attention toward the topic. (Da et al., 2011) contend that SVI is a more direct channel of retail investor attention as searching for a topic implies attention to the topic. As "Sea Level Rise" is very specific, the search volume data are sparse and are only available for 36 countries of the total 65 country sample. I remove the SVI indices of two countries, Argentina and Slovenia, as zeroes comprise more than 90% of their observations which leaves a total sample size of 34 countries. While a broader topic may be available for the full sample of countries, I argue that "Sea Level Rise" is more salient in the context of this paper.

3 Empirical Tests

3.1 Surge Events and Sovereign Risk

I begin by validating that surge events negatively impact the creditworthiness of sovereigns. This step is critical as prior work by Cavallo et al. (2013) find no negative effect on the economic growth of countries after extremely large disasters. On the other hand, work by Chang et al. (2021) shows causal evidence of the negative effect of the Japanese tsunami of 2011 on sovereign risk and trade linkages. While these two papers have differing results on the actual economic impact of disasters, a parallel idea is the *perception* of these risks by investors (Krueger et al., 2020). In principal, a large enough coastal flood should deteriorate the credit quality of a region in the short term and alert investors to potential future surges.

The econometric identification of interest is a panel ordinary least squares regression with time and country-fixed effects for a sample of countries that have had historical exposure to coastal flooding. After matching the data from EM-DAT and Dartmouth Flood Observatory to my sample of CDS spreads, there are 16 coastal flooding disasters for 16 different countries.[14] Similar to Eisensee and Strömberg (2007), I consider surge disasters and their respective fallout severity as reasonably exogenous events.

I narrow down the 65 countries in the original sample to the 16 that have experienced flooding events to retain a relatively comparable set of regions. Specifically, I

[14] The full description of the data gathering technique is found in Section 2.2.

project monthly percentage changes in sovereign CDS spreads onto the binary variable, $Surge_{i,t}$, which takes on a value of one if a country experiences a surge event and zero if it has not. This is formally defined is:

$$\Delta CDS_{i,t} = \alpha + \beta_1 Surge_{i,t} + \gamma \Delta X_{i,t} + \eta_i + \lambda_t + \varepsilon_{i,t}, \tag{2}$$

where ΔCDS_{it} is the monthly growth in sovereign CDS in the 1-, 5-, or 10-year spread for country i at time t. The base covariates, $\Delta X_{i,t}$, are a set of country and global specific factors inferred from prior literature Augustin (2018). The global covariates are the change in the 5 year constant maturity Treasury yield, the change in CBOE VIX volatility index, and the SP 500 excess returns. The local covariates include the changes in the exchange rate of the local currency to USD, changes in foreign currency reserves denominated in USD, and local MSCI excess stock returns. The variable η_i represents country-fixed effects to capture unobserved country heterogeneity, λ_i signifies time-fixed effects, and $\varepsilon_{i,t}$ is the residual. The primary coefficient of interest is β_1, which is the elasticity of storm surges and growth in sovereign CDS spreads.

In the regression, β_1, should be highly sensitive to the severity of the event (Eisensee and Strömberg, 2007). Realistically, small-scale disasters that affect a handful of individuals should not be salient to the sovereign credit risk of these regions and will not impact the equilibrium price of sovereign CDS spreads. This is corroborated in disaster models where country GDP contracts by 10% or more after an event Barro and Ursua (2008). Therefore, I subset the 16 shocks into two separate indicators: (1) capturing the disasters above the 90th percentile that results in two events, and (2) the 95th percentile which leads to representing one surge catastrophe. The two include the 2017 southern Thai flood and the larger 2013 typhoon that hit the Philippines. The results of the regression when $Surge_{i,t}$ is equal to one to indicate the two events is presented in the left panel of table 5, while the right panel represents the same regression with the indicator set to one for largest flood - the 2013 typhoon in the Philippines.

The results in the left panel suggest a positive and significant relationship between sovereign risk and large coastal flooding events. (CHECKOVER) Columns 2 and 3 contain significant indicates that reasonably disastrous surges will increase a country's 5 and 10-year sovereign CDS spread by 4.77% and 3.90%. The first column points to a positive coefficient, however, the large standard errors subsume it's significance. In right panel, I find positive and significant coefficients across the term structure of sovereign CDS spreads. A catastrophic coastal flood contemporaneously increases the 1 year spread by 24.39% and the 10-year spread by 4.95%. While there is a considerable limitation of minimal observations in this sample, the results support hypothesis H_1 and suggest that sovereign credit risk increases after catastrophic coastal surges. This result that natural disasters affect the credit-worthiness is corroborated by Chang et al. (2021) who find a drop in the credit quality of Japan after the 2011 earthquake which triggered a tsunami.

I examine the results more carefully by comparing the coefficients across the term structure. To understand the economic significance of the binary variable of interest, I divide the *Surge* coefficients by the respective standard deviations for each sovereign CDS tenor for the right panel of Table 5. This results in sizes of 54.03%, 33.98%, and 32.14% in order from the fourth to the sixth columns.[15] The findings are in line with Hypothesis H_1 that disasters have a prominent effect on the short-term credit risk of a country. These results are similar to the conclusions in Augustin (2018) who find that domestic credit shocks can affect the term structure of sovereign credit risk. The typically positive slope in the term structure of default risk (Pan and Singleton, 2008) is flattened because of the disaster. Overall, my analysis points to a deterioration in the credit quality of sovereigns after they experience a domestic coastal flood – consistent with hypothesis H_1.

The significant coefficients for the longer tenors also suggest that disasters alert investors to the disaster risk of future coastal flooding events. Investors are likely to focus on attention grabbing natural disasters due to their limited attention (**?**). The sudden shock shifts the beliefs of many investors who then demand insurance for future events and thus raise the equilibrium price for insurance (Giglio et al., 2021).

The results presented in this section are consistent with hypothesis H_1 and set the stage to test whether the sovereign CDS market is accurately accounting for *stock* and *trend* SLR risk. Sufficiently large coastal flooding events raise the sovereign risk of affected countries in the short-term. The preliminary results also suggest that investors' tastes for insurance against longer term risks are also lifted which is in line with the reasoning outlined by Weitzman (2012). Thus, I next test whether investors account for differential exposure to SLR during periods of heightened attention and fear.

[15] The standard deviations for the 1-, 5-, and 10-year terms are 45.14, 20.10, and 15.40, respectively. The means and standard deviations for the sample can be found in Panel A of Table 3.

3.2 Global Attention

In this section of the empirical analysis, I test the relationship of worldwide attention to global warming and climate adaptation on sovereign credit risk. The two indices of Faccini et al. (2021) can be deemed as reasonable proxies for investor attention and I consider them similar to global factors that drive investors' appetite for credit exposure as in Pan and Singleton (2008). Through this lens, I conduct time series analysis to examine if attention indices ($Attention_t$) have power in explaining the growth of sovereign CDS spreads (ΔCDS_{it}) across time. Akin to Dieckmann and Plank (2012), I estimate the following panel regression with country-fixed effects:

$$\Delta CDS_{i,t} = \alpha + \beta_1 Attention_t + \gamma \Delta X_{i,t} + \eta_i + \varepsilon_{i,t}, \tag{3}$$

where the notation is similar to equation 2 but with two differences. First, the time-fixed effects are removed to assess the time-series dynamics of attention. Second, the variable $Attention_t$ is added which only possesses a time-series component and can represent attention to global warming or climate adaptation.

The main identification strategy exploits the differential exposure to *stock* SLR found in table 4. Specifically, I subset the entire 65 country sample into quintiles of exposure where the fifth are the countries most exposed and the fourth through the first are the least exposed to *stock* SLR risk. This methodology places the 13 countries most vulnerable into one category and the remaining 52 into the least exposed category. I argue that this methodology is sensible as vulnerability is heavily skewed to the top quintile and precipitously falls into the fourth quintile. The sample statistics of the two groups are presented in Panel B of Table 3 where it is shown that there is no significant difference between the two samples across all maturities.

The first index that I employ, adaptation risk, should positively be linked to sovereign risk as building infrastructure is expensive. Furthermore, the raised attention towards adaptation could indirectly alert investors to the risks of SLR. I separate the differentially exposed sample and conduct panel regressions in equation 3 with the adaptation index, the results of which are presented in table 6. None of the coefficients for the adaptation index are significant at any level in the least exposed sample and only columns 2 and 3 have marginally positive coefficients. The results are consistent with part of hypothesis H_2 that investors do not insure against countries that are least exposed to *stock* risk.

By comparison, the coefficients for the index in columns 5 and 6 are positive and significant at the 1% level, further validating the remaining hypothesis. Specifically, a one standard deviation increase in the adaptation index is related to a rise of 0.84% in the growth of the 10-year CDS (7.8% of the tenor's standard deviation) for vulnerable countries.[16] An equivalent increase in the index is associated with a comparable growth of 0.86% for the 5 year CDS (6.0% of the 10-year contract's standard deviation). Since the term structure of sovereign CDS spreads are typically upward sloping, adaptation risk appears to be more relevant in the long-term.[17] This is logical as infrastructure construction projects to protect against SLR can take decades to build, leaving the country to accept their current exposure to *stock* risk.[18] This finding strongly supports hypothesis H_2 that investors will insurance against adaptation risk for countries exceedingly exposed to *stock* SLR risks.

The second index I highlight is attention to global warming where the expectation is that increased attention should alert investors to corollary risks such as SLR. The results of the regressions for least exposed countries are shown in the left panel of 7. The coefficients in the panel progressively increase with the maturity of the sovereign CDS spread, which can be interpreted as global warming being a risk for countries irrespective of their exposure to SLR. Global warming incorporates a general rise in temperatures and other environmental risks that are clear threats to the long-term economic well-being of all countries (Weitzman, 2009). The positive coefficient implies that investors insure against this risk over the long run.

In contrast, the right panel demonstrates significant positive coefficients across the entire term structure of sovereign spreads for countries that are highly exposed to SLR. A one standard deviation increase in the global warming index results in a 2.1% increase in the 1 year CDS spread (5.6% of the variable's standard deviation). Similarly, a one standard deviation increase in the index is associated with a 0.63% higher growth rate for the 5 year CDS spread (4.4% of the standard deviation of the spread). The economic significance is largest in column eight where a one standard deviation increase of attention is associated with a 0.77% increase in the 10-year spread (7.2% of the standard deviation of the 10-year spread). To explicitly check if the coefficients for global warming are different for columns 3 and 8, I conduct a Chow test which results in an F statistic of 5.23 (significantly different at the 5% level or better). Collectively, the results support hypothesis H_2 in that investors seek to

[16] The standard deviations are found in Panel B of Table 3.

[17] Simply explained, a rise in the growth of the 10-year CDS spread is more meaningful for long-term sovereign risk when compared to an equivalent increase for the 5 year spread.

[18] The Delta Works project took more than four decades to build.

insure against *stock* SLR risk during a heightened period of attention to warming.

Taken together, the findings present evidence of the changing price of sovereign insurance contemporaneously with global attention to adaptation and global warming risk. In contrast to the short-term effects of idiosyncratic surge events in Section 3.1, longer horizon maturities are most affected when investors perceive SLR risk. Faced with investments that are exposed to fat-tailed climate damages, investors purchase long horizon investments that are valuable when consumption falls after a surge shock. This is in line with previous literature that find market attention as a key driver of long-term assets that are vulnerable to SLR (Painter (2020); Giglio et al. (2021), Bernstein et al. (2019); Baldauf et al. (2020); Goldsmith-Pinkham et al. (2021)).

When comparing the economic effect sizes, the results suggest that investors insure against adaptation risk to a greater degree than global warming risk for countries that are most affected.[19] A simple explanation is that adaptation is more directly related to sovereign risk of *stock* exposed countries as the samples are split on the differential exposure to SLR risk. Global warming, in contrast, has a more diffused and broad effect on regions globally. Nonetheless, the results give credence to the literature that find sovereign credit risk is driven by global risk factors (Pan and Singleton (2008); Longstaff et al. (2011); Augustin and Tédongap (2016)).

3.3 Local Attention

I continue the empirical investigation by testing whether local attention to SLR is related to sovereign risk. In a prior section (3.1), I find that particularly devastating surge events for specific countries can cause longer-term sovereign risk to spike. The likely mechanism is that the locally experienced shock changes investors' preferences for insurance to protect against future events. Here, I more directly test whether local attention to SLR changes the equilibrium price of insurance. Consistent with Hilscher and Nosbusch (2010) and Augustin et al. (2016), I view country-level attention as a potential risk factor that can alarm investors to *stock* risk.

Data gathered from country Google search volumes (SVI) on the topic "Sea Level Rise" are used to proxy for local investor attention, akin to Choi et al. (2020). As described in Section 2.5, the SVI index does not exist for every country in the full sample of 65 countries and instead is only available for 34 countries. One of the unavailable countries, Egypt, is found in the most exposed sample while the remaining unobtainable countries are in the least exposed. While the use of the index does limit

[19] Here I am comparing relative sizes of a one standard deviation increase in both variables.

the sample size, I maintain that the two groups are still comparable as the group of interest remains mostly unchanged. To be thorough, I compare the two groups across all maturities, the results of which are presented in Table 3, and find no significant difference between them.

I assign the country-specific indices to equal one when above or equal to the 95th percentile and zero otherwise. This results in an indicator variable that represents a particularly high period of attention in a country to SLR. For the 1-, 5-, and 10-year sovereign CDS spreads ($\Delta CDS_{i,t}$), I estimate the beta (β_1) on the country level SVI index ($Attention_{i,t}$) for country i over each month t as follows:

$$\Delta CDS_{i,t} = \alpha + \beta_1 Attention_{i,t} + \gamma \Delta X_{i,t} + \lambda_t + \varepsilon_{i,t}. \tag{4}$$

The control variables used in the prior regressions are employed here. The difference is the inclusion of λ_i which represents year by month-fixed effects to capture observable and unobservable heterogeneity between periods. The inclusion of time-fixed effects allows for the investigation of country-specific attention on sovereign risk.

The first row of Table 8 presents the betas (β_1) estimated for each of the two samples and across the term structure. The left panel presents non-significant coefficients for the SVI indicator, with the only positive association for the 5 year sovereign CDS spread. In contrast, the highly exposed countries (right hand panel) present positive coefficients, with significance for the 5th and 6th columns (significantly at the 10% level or better. The results thus far indicate a positive but modest relationship between country-level attention to the topic "Sea Level Rise" and sovereign risk.

To continue interpreting the results, I compare the estimated betas across the term structure for the most exposed sample. During particularly elevated periods of attention to SLR, there is a 1.53% increase in the 10-year sovereign spread (or 14.33% of the spread's standard deviation). There is a near equivalent rise of 1.85% in the 5 year spread - or 13.06% of the 5 year spread's standard deviation. Finally, the 1 year CDS growth rate increases by 3.34% that corresponds to 8.70% of the variable's standard deviation. These results imply that local attention has a marginally more meaningful impact on longer term sovereign risk which supports hypothesis H_2. Periods of extremely high attention toward SLR in a country, shift investors' tastes for purchasing insurance against the *stock* risk of SLR.

The evidence produced show that while local attention does shift investors demand for insurance against countries most affected, the effect is modest in comparison to global attention. Only extremely elevated periods of local attention shift sovereign

CDS spreads. Lower threshold values of local attention are tested; however, only attention at the 95th percentile and above are found to be significantly positive.[20] These findings are consistent with Ang and Longstaff (2013) and Pan and Singleton (2008) who find global financial variables are the primary drivers of sovereign risk. Nonetheless, I do find some evidence of domestic attention associated with sovereign credit quality similar to Augustin (2018) and Hilscher and Nosbusch (2010).

At this stage, I find support for both hypotheses H_1 and H_2. Catastrophic surge events degrade the credit-worthiness of countries affected. To insure against such a risk, investors purchase sovereign insurance for countries that are exposed during moments where global and local attention to SLR risk is high. Sovereign CDS insurance contracts are a simple method to hedge against bad states of the world which make them appealing for investors that are fearful of extreme climate change events.

3.4 Trends in Flood Exposure

In this section, I conduct empirical tests to study whether investors are accounting for trends in surge exposure. I split high *stock* exposure countries into most and least exposed samples using the trends calculated in section 2.4. The *trend* exposure is obtained from country-specific AR(1) models augmented with a trend term (γ_c in equation 1), similar to that of Hong et al. (2019). Historical *trend* exposure is calculated from backward-looking data on country exposure to SLR, whereas future exposure is calculated using forward looking, climate model data on land area that will be inundated by 1-in-100 year coastal floods under RCP 4.5. I then overlay populations forecasted to be living in the same flood zone to understand which countries will have greater or lesser exposure in the future.[21].

To test hypothesis H_3, I again use global attention indices as the primary independent drivers for time-series variation. Since the prior empirical results presented the salience of global attention over local, I discard the country-level SVI indices. I create a larger sample set by selecting the fourth and fifth quintiles of *stock* exposure found in Table 4; the remaining countries are removed from the analysis as their *trend* exposure would only marginally increase SLR risk. Furthermore, I remove Vietnam from the sample as its *stock* exposure is more than four times the standard deviation of the top two quintiles.[22] The remaining 25 countries are then split into a most

[20]Threshold values of the 75th and 90th percentile were tested, but, the coefficients of SVI were positive but not significant in the sample of highly exposed countries.

[21]For a more thorough explanation, please read section 2.4

[22]In this case, I want to compare samples that have similar *stock* exposures but are differentially

and least exposed sample by sorting countries based on $HTREND$ and $FTREND$ which are the γ_c's respectively calculated from historical and future climate data. Once again, I conduct two sample t-tests to find no significant difference between the groups as presented in Panel D and E in Table 3.

Table 9 presents the results for the historical (Panel A) and future (Panel B) trends in SLR. The top sections of both panels contain the countries which are vulnerable to rising *trend* exposure, whereas the bottom section comprises of countries with declining exposure. The second and third columns for each panel contain the calculated trend term and the respective p-value from the country AR(1) model from equation 1. To verify that the exposed and unexposed samples are equivalent in *stock* exposure when using $HTREND$ or $FTREND$, I perform two separate t-tests which result in no significant difference between improving/worsening trend groups. Using the differential in $HTREND$ and $FTREND$, I conduct various regressions, in the form of equation 3, with the 10-year sovereign CDS as the dependent variable. The expectation, in line with hypothesis H_3, is that investors should insure against countries that will be exposed to worsening SLR trends, therefore, increasing the sovereign risk of the country in the long run.

The results of the various regressions are presented in Table 10 where the left and right panels comprise of the sample according to $HTREND$ and $FTREND$, respectively. The first row represents the coefficients when using the adaptation index, while the second row presents estimates from the global warming index. The columns alternate the sample, first showing the estimates for the improving countries and then displaying the same for the worsening countries. Counter-intuitively, the coefficients are smaller for countries that have worsening trends rather than improving trends. In the left panel, a one standard deviation increase in the adaptation index is associated with a 0.52% rise in the growth of the 10-year CDS spread (4.6% of the variable's standard deviation) for countries with a worsening trend. In contrast, the same increase leads to a 0.67% rise in the 10-year spread (6.06% of the 10-year spread's sample standard deviation). The global warming index suggests similar results in that countries with improving trends are being insured against.

The counterintuitive results are more apparent in the right-hand panel which relies on future trends. Countries with improving SLR trends have large significant coefficients for the attention indices compared to their counterparts. I conduct Chow

exposed in *trend* exposure. Including Vietnam will make the groups incomparable due to its status as an outlier.

tests to identify whether there are significant differences in the attention coefficients between the improving and worsening countries. The results indicate that there are no significant differences between the two samples (at the 10% level or better). Taken together, the evidence suggests that investors are not accounting for *trend* SLR risk which refutes hypothesis H_3.

In contrast to the prior findings that *stock* vulnerability is priced in sovereign CDS markets, the results here suggest that investors are inaccurately accounting for *trend* exposure. This aligns with the findings from Hong et al. (2019) and Murfin and Spiegel (2020) who find that trends in climate risks are not priced in markets. Murfin and Spiegel (2020), who use differential exposure of real-estate to trends in SLR to investigate a potential pricing effect, find no additional premium for properties that are experiencing a faster rate of SLR. One explanation the authors provide for the non-finding is a limited understanding of the risks of SLR. This resonates with the findings of this paper as the speed of SLR is a difficult concept to incorporate into markets because of the relative complexity of climate models. Investors, who have limited attention, are careful of the aggregate exposure of regions to *stock* SLR but do not consider the more sophisticated risk of increasing rates.

4 Robustness Checks

4.1 Infrastructure Protection

The prior results demonstrate that investors are insuring for *stock* SLR exposure. In each test, countries that are currently protected against 1-in-100 year surge events are placed in the less exposed sample. As a robustness check, I empirically test if countries that have built infrastructure to combat SLR are experiencing increased sovereign risk. The expectation is that investors should not purchase insurance for countries that have built levees or dikes, leaving the sovereign CDS spreads unaffected.

I select the countries from the sample of 65 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 3, 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 first three columns include the adaptation index whereas the last three use the global warming index.

None of the coefficients in the first two rows are significant at the 10% level or better, suggesting that heightened global attention does not lead to investors insuring against countries that are reasonably protected.

To delve into the results, I find that a one standard deviation increase in the adaptation index is related to a 0.84% increase in the growth of the 1 year spread (or 2.14% of the variable's standard deviation). Likewise, the same rise in the adaptation index is associated with a 0.15% higher value for the 10-year maturity growth rate (1.2% of the variable's standard deviation). Generally, the effect sizes are small and insignificant across the term structure. The results are comparable when using the global warming index but with more emphasis over the long horizon. While the coefficients are still insignificant, this could be interpreted as investors placing more weight on the negative consequences of rising temperatures and global warming in general. In aggregate, the findings indirectly support hypothesis H_2 in that investors are accurately accounting for *stock* risk while respecting country protection standards.

4.2 Sovereign CDS Trades

The evidence provided thus far implicitly test for investor attention to SLR as there would be no observed price reaction for sovereign CDS spreads if investors did not pay attention. The implied mechanism is that investors react to adaptation, SLR, and global warming risks by purchasing insurance against countries that have greater exposure that, in turn, increases the equilibrium price of the sovereign CDS. In this case, I do not explicitly link investor behavior of purchasing more insurance that I attempt to rectify in this robustness check.

To investigate investor trading of sovereign CDS, I follow the prior work of Augustin et al. (2016) who identify the primary drivers of trading in this market. They use weekly data from the Depository Trust and Clearing Corporation (DTCC) who provide gross notional amounts and trading frequencies of single-name sovereign CDS. Similarly, I obtain data that contains average new gross notional amounts and trading volume for entities with contracts that have greater than 50 transactions, both are reported at a weekly frequency from January 1st, 2010 to March 25th, 2016. The gross notional amount represents the sum of CDS contracts bought (or sold) across all tenors for a single reference entity in the Trade Information Warehouse database.[23] The gross notional outstanding is the underlying reference amount used to calcu-

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

late the spread and the total recovery amount when a default of a sovereign occurs. New trades simply represent the number of contracts traded (bought or sold) over the weekly period. Jointly, the two series provide a practical means to understand whether there is elevated trading activity during periods of attention that would further substantiate the increased spreads found in the main results.

As a consequence of the previous evidence that global attention is material to investors, I use the adaptation and global warming factors developed by Faccini et al. (2021). To match the DTCC data, I transform the attention indices by averaging the daily series to the Monday to Friday weekly average. I also transform the trade and gross notional data by generating the weekly percentage growth for both series to match CDS spread exercises. The sample is restricted to only include countries that have more than 80% of their observations as non-missing and different from zero. This leaves the 13 original fifth quintile countries as the exposed sample and 38 countries from the other quintiles as the unexposed sample.[24] I then project the two growth series onto the attention indices with country fixed-effects, year by month fixed-effects and robust standard errors to obtain a set of models, the results of which are presented in Table 12. Here, the goal of the fixed-effects are to remove omitted variable bias across countries, months, and years to leave the within-week variation.

In both panels of Table 12 the dependent variable is alternated with the percentage growth in trades and gross notional amounts. The sole positive and significant coefficient in the least exposed panel is in the third column that shows a coefficient of 91.45 for the adaptation index. Economically, a one-standard deviation increase in the adaptation index (0.28) is associated with a 25.65% increase in the number of weekly contract transactions that occur. However, the coefficient for the adaptation index is negative and non-significant in the fourth column that corresponds to the growth in gross notional amount as the dependent variable. In contrast, the regression coefficients in the most exposed sample for the adaptation index are both positive and significant. A one-standard deviation increase in the adaptation index is related to a 47.58% rise in the number of contract trades and a 106.63% increase in the gross notional amount traded. The results suggest that investors purchase insurance against highly exposed *stock* countries by entering into new contracts that increase the gross notional outstanding. Collectively, the findings indicate that investors could be exiting CDS contracts from lesser exposed countries to more exposed ones.

[24]The countries that are removed from the less exposed sample are Bahrain, Cyprus, Ghana, Hong Kong, Jamaica, Malta, Uruguay, Dominican Republic, Guatemala, Lebanon, Sri Lanka, Serbia, Trinidad and Tobago, and El Salvador.

The coefficients for the global warming index for the least exposed countries are non-significant with negative signs which is contrary to the results of Table 7 that show a positive relationship with the 10-year CDS maturity. One explanation for this incongruous finding could be due to the limited sample size of the DTCC data in comparison to the CDS spread data. Additionally, the trade and notional data constitute the *aggregate* of CDS contracts traded across all maturities which may offset the increased premium seen in the longer term spread. Conversely, the coefficients for the global warming index are positive for the highly exposed countries but remain non-significant. This non-significant result could be due to the weaker relationship between the global warming index and the growth in sovereign spreads as discovered in section 3.2. Nonetheless, the dynamics presented suggest that investors purchase insurance for exposed countries during periods of increased attention to adaptation and global warming (to a lesser extent) that supports hypothesis H_2.

The evidence provided in this section largely points to increased sovereign default insurance bought during periods of attention to adaptation risks which parallels the prior findings. I explicitly show that CDS market activity is positively associated with global attention for countries that are exposed to *stock* SLR. This interpretation is in line with the findings of Augustin et al. (2016) who show that investors use sovereign CDS primarily as hedging instruments. While there is generally a positive relationship between global warming attention and sovereign default insurance activity, the association is non-significant. The conclusions drawn from this investigation explicitly support the results that the cost of insurance rises to protect against countries that are most exposed during periods of global attention to SLR risks.

5 Conclusion

In this paper, I adopt a disaster asset-pricing perspective to document that investors view sea level rise as a form of disaster risk and accordingly buy sovereign insurance to protect their investments. To substantiate this claim, I present evidence that catastrophic surge events significantly deteriorate the creditworthiness of affected countries. I use sovereign credit default swap (CDS) spreads of 65 countries throughout the investigation as a measure to evaluate credit health and insurance cost for a sovereign. Amongst a subset of countries that have experienced SLR disasters, destructive coastal surges increase the growth of 1- and 10-year sovereign spreads by 24.39 and 4.95 percent, respectively. Therefore, according to theory, investors who are fearful and whose investments are affected by potential losses in consumption should purchase insurance—driving up the equilibrium spreads of sovereign CDS contracts.

Due to the infrequent nature of coastal surge events, I use global and local attention indices that possess substantial time-variation to study the effects of attention on the growth of 1-, 5-, and 10-year CDS spreads. The two global indices represent news concerning country adaptation to climate change and global warming in general. I use Google search activity for "Sea Level Rise' as a country-level attention proxy. My primary identification strategy leverages the differential exposure of countries to coastal flooding in the last two decades—what I call *stock* exposure. I find that heightened fear of adaptation risks and global warming prompts investors to purchase insurance against 13 vulnerable countries rather than for ones less exposed. In contrast, local attention is only significant and positively associated with longer maturities when attention is above two standard deviations. These results align with Weitzman's view that investors who are faced with a low consumption world due to tail-risk climate events will hedge this risk, thereby increasing the cost of insurance.

While I present compelling evidence that investors look to current coastal flooding exposure to discipline their investments with insurance, I find little indication that they account for future *trends* of SLR, subsidence, or population movement to the coast. Specifically, I use the differential exposure of countries to *trend* SLR risk by measuring trends of population exposure for each country with historical and future geospatial data on SLR, subsidence, and populations. The findings suggest that investors are not accurately accounting for exposure trends either when using historical or recently developed climate model data.

To further support these findings, I confirm that countries that have already built infrastructure to protect against large surge events are unaffected by this sovereign risk. Simply, investors are accounting for countries that have already invested in substantial SLR protection. I also explicitly check if there is increased sovereign CDS trading activity during periods of heightened global attention. In accordance with the prior evidence, I show that trading activity and gross notional amounts of sovereign CDS contracts increase with elevated attention to adaptation and global warming.

The results have substantial implications for policymakers. Countries exposed to SLR will be driven to build resilient infrastructure with public finance such as government bonds. However, as sovereign risk increases with the perception of coastal flooding, government debt will also become more expensive to issue. Both factors will place undue pressure on the finances of highly affected countries.

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6 Tables

Table 1. Glossary

Term	Description
CDS	Credit default swap.
SLR	Sea level rise.
Stock Exposure	The population of a country that is exposed to coastal flooding in the last two decades (2000-2019).
Trend Exposure	Whether a country has an increasing or decreasing rate of SLR exposure either calculated with historical or future trends in population and SLR inundation.
HTREND	The trend exposure of a country obtained from an AR(1) using population of the country exposed to a 1 in 100 year flood over the years 2000-2019.
FTREND	The trend exposure of a country obtained from an AR(1) using population of the country exposed to a 1 in 100 year flood over the years 2010-2100 in 10 year steps.
Gross Notional	Aggregate gross notional amount of CDS outstanding which is sum of CDS contracts bought (or sold) for all contracts. This is in millions of US dollar equivalents using foreign exchange rates.
Trades	New CDS contracts traded (bought or sold).
Google SVI	Google search volume index on the topic Sea Level Rise, obtained for as many countries as possible in the sample.

Table 2. Summary Statistics

	Mean	SD	p25	p50	p75	N
% Δ 1 Year Sovereign Spread	3.69	39.19	-14.01	-0.09	12.49	7680
% Δ 5 Year Sovereign Spread	0.34	15.24	-6.87	-0.24	4.77	7680
% Δ 10 Year Sovereign Spread	0.34	12.70	-5.01	-0.21	3.58	7680
S&P 500 Returns	0.94	3.59	-1.35	1.31	3.03	7735
MSCI Index Returns	0.13	6.57	-3.51	0.05	3.86	7729
% Δ International Currency Reserves	16.71	1423.97	-1.43	0.18	1.94	7735
% Δ Exchange Rate to USD	0.34	2.44	-0.59	0.02	1.09	7735
% Δ VIX	2.07	24.37	-14.60	-2.13	10.93	7735
% Δ US 5 Year Treasury	0.35	11.59	-6.64	0.00	5.97	7735
Adaptation Index	0.30	0.19	0.14	0.26	0.41	7735
Global Warming Index	0.35	0.22	0.19	0.30	0.45	7735
Google Search Index "Sea Level Rise"	6.56	12.62	0.00	0.00	8.00	4284
Total Affected in Surge Events	1,463,498.00	4,616,077.00	713.00	15,030.00	358,303.00	16.00
% Growth CDS Trades	133.03	598.88	(50.00)	-	88.89	8,235.00
% Growth Gross Notional Amount	313.48	3,529.12	(53.40)	(1.42)	106.81	8,235.00

Table 2 presents summary statistics reported at the country-month level. The total sample includes 65 countries between the periods January, 2010 through November, 2019.

Table 3. Sample Statistics: Exposed vs Unexposed

Panel A

Surge Events	Mean	SD
Δ 1 Year Sovereign Spread	5.31	45.14
Δ 5 Year Sovereign Spread	0.74	20.10
Δ 10 Year Sovereign Spread	0.56	15.40

Panel B

Global Attention	Less Exposed		Highly Exposed		Two -Sample T-test
	Mean	SD	Mean	SD	P Value: Diff > 0
Δ 1 Year Sovereign Spread	3.59	39.66	4.09	37.26	0.68
Δ 5 Year Sovereign Spread	0.42	15.47	0.05	14.28	0.18
Δ 10 Year Sovereign Spread	0.41	13.15	0.07	10.72	0.14

Panel C

Local Attention: Google SVI	Less Exposed		Highly Exposed		Two -Sample T-test
	Mean	SD	Mean	SD	P Value: Diff > 0
Δ 1 Year Sovereign Spread	3.88	35.79	4.28	38.37	0.63
Δ 5 Year Sovereign Spread	0.27	14.41	-0.02	14.46	0.27
Δ 10 Year Sovereign Spread	0.22	11.08	-0.01	10.68	0.25

Panel D

Historical Trend: HTREND	Improving		Worsening		Two -Sample T-test
	Mean	SD	Mean	SD	P Value: Diff > 0
Δ 10 Year Sovereign Spread	-0.01	11.05	0.05	10.83	0.68

Panel E

Future Trend: FTREND	Improving		Worsening		Two -Sample T-test
	Mean	SD	Mean	SD	P Value: Diff > 0
Δ 10 Year Sovereign Spread	-0.06	10.32	0.14	11.77	0.56

Table 3 presents the mean and standard deviation of the percent growth for the 1-, 5-, and 10-year sovereign CDS spreads. Panel A shows the statistics for the 16 countries that experienced flooding disasters which are used in the analysis in Section 3.1. Panel B illustrates the differences between the less and highly exposed samples when using the global attention indices in Section 3.2. Panel C displays the sample statistics for the less and highly exposed samples when using the local Google Search index in Section 3.3. Panel D and E exhibit the sample statistics for countries with improving or worsening trends in sea level rise when using historical and projected climate model data for use in Section 3.4. Panels B, C, D, and E show the non-significant p-values for two-sample T-tests between the two groups.

Table 4. *Stock* and Quintile Exposure for Sovereigns

Full Name	Perc Exposed	Quintile	Full Name	Perc Exposed	Quintile
Vietnam	16.69	5	Estonia	0.03	3
Belgium	7.18	5	Uruguay	0.02	3
China	3.19	5	Costa Rica	0.02	3
Egypt	2.67	5	Morocco	0.01	3
Germany	2.36	5	Panama	0.01	3
Denmark	2.26	5	Turkey	0.01	3
United Kingdom	2.24	5	Dominican Republic	0.01	2
Norway	2.13	5	Chile	0.01	2
Japan	1.81	5	Slovenia	0.00	2
Finland	1.57	5	Peru	0.00	2
Indonesia	0.96	5	Cyprus	0.00	2
France	0.96	5	Sri Lanka	0.00	2
Thailand	0.90	5	Trinidad and Tobago	0.00	2
Sweden	0.75	4	Lebanon	0.00	2
Poland	0.50	4	Guatemala	0.00	2
Lithuania	0.48	4	South Africa	0.00	2
Croatia	0.26	4	Italy	0.00	1
Latvia	0.26	4	Netherlands (the)	0.00	1
Philippines	0.26	4	Bahrain	0.00	1
Republic of Korea	0.20	4	Bulgaria	0.00	1
Ghana	0.18	4	Hungary	0.00	1
Ireland	0.17	4	Slovakia	0.00	1
Russia	0.11	4	Israel	0.00	1
Malaysia	0.09	4	Romania	0.00	1
Brazil	0.09	4	Ukraine	0.00	1
Portugal	0.07	4	Qatar	0.00	1
New Zealand	0.06	3	Serbia	0.00	1
Mexico	0.04	3	El Salvador	0.00	1
Argentina	0.04	3	Hong Kong	0.00	1
Jamaica	0.04	3	Czechia	0.00	1
Colombia	0.03	3	Austria	0.00	1
Australia	0.03	3	Kazakhstan	0.00	1
Spain	0.03	3			

Table 4 presents *stock* exposure for countries after averaging the yearly population exposure over 2000 through 2019. I gather gridded data at the 1 km by 1 km resolution from LandScan which provides historical population data from 2000 through 2019 and 1 in 100 year surge exposure data from Muis et al. (2016). I consider a 1 km square grid to be inundated if surge height tops 30 cm. The left and right columns represents the highest to lowest exposed countries in order. I set exposure to zero for countries with 1 in 100 year surge protection standards (Lincke and Hinkel, 2018). The right most column of both panels represent the quintile of exposure.

Table 5. Coastal Surges and Sovereign Risk

	90th Percentile			95th Percentile		
	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
Surge	12.22	4.77**	3.90***	24.39**	6.83**	4.95*
	(10.02)	(2.11)	(1.42)	(10.67)	(3.37)	(2.55)
MSCI Local Returns	-2.72***	-1.29***	-0.95***	-2.72***	-1.29***	-0.95***
	(0.79)	(0.45)	(0.34)	(0.79)	(0.45)	(0.34)
Exchange Rate Dollar	2.16	1.50*	1.18*	2.16	1.50*	1.18*
	(1.40)	(0.81)	(0.61)	(1.40)	(0.81)	(0.61)
Intl Reserves	-0.75*	-0.33	-0.29	-0.75*	-0.33	-0.29
	(0.43)	(0.24)	(0.18)	(0.43)	(0.24)	(0.18)
Observations	1756	1756	1756	1755	1755	1755
R^2	0.406	0.438	0.429	0.406	0.438	0.429

Table 5 presents regressions estimated with equation 2. The regressions are estimated with both year by month and country fixed effects. Surge is a 0/1 indicator variable which represents either the 90th percentile of surge events (left panel) or the 95th percentile of surge events (right panel). The global financial variables, VIX, 5 year Treasury, and the SP 500 returns are dropped due to the time fixed-effects. The events in left panel include the 2017 southern Thailand flood and the 2013 typhoon which hit the Philippines. Panel B only represents the two-sigma Philippine typhoon. Each panel reports the regression coefficients of the growth in sovereign CDS spreads in the 1-, 5-, and 10-year maturities.Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Time Series Regressions: Adaptation

	Less Exposed			Highly Exposed		
	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
Adaptation	-0.919	0.063	0.810	6.788	4.474***	4.372***
	(2.377)	(0.922)	(0.804)	(4.321)	(1.664)	(1.357)
SPX Returns	-1.332***	-0.749***	-0.635***	-2.180***	-1.099***	-0.883***
	(0.297)	(0.148)	(0.121)	(0.401)	(0.162)	(0.133)
MSCI Local Returns	-1.375***	-0.694***	-0.543***	-1.686***	-0.813***	-0.571***
	(0.181)	(0.087)	(0.069)	(0.194)	(0.085)	(0.072)
Exchange Rate Dollar	1.397***	0.846***	0.559**	-0.407	0.020	0.020
	(0.522)	(0.290)	(0.225)	(0.311)	(0.236)	(0.176)
Intl Reserves	-0.173	0.027	0.049	-0.000***	0.000***	0.000***
	(0.144)	(0.068)	(0.093)	(0.000)	(0.000)	(0.000)
5 Yr Treasury	0.122**	0.009	0.001	0.239***	0.016	-0.004
	(0.050)	(0.023)	(0.019)	(0.083)	(0.031)	(0.023)
VIX	0.028	0.007	0.002	-0.006	-0.025	-0.027*
	(0.025)	(0.010)	(0.008)	(0.062)	(0.022)	(0.016)
Observations	6127	6127	6127	1547	1547	1547
R^2	0.133	0.233	0.195	0.165	0.264	0.253

Table 6 presents regressions estimated with equation 3. The regressions are estimated with only country fixed effects to investigate the relationship between the adaptation index (Adaptation) and sovereign risk. The Less Exposed panel consist of countries in quintiles four through one in Table 4 whereas the Highly Exposed panel contains the fifth quintile countries. Both global and local financial variables are kept. Each panel reports the regression coefficients of the growth in sovereign CDS spreads in the 1-, 5-, and 10-year maturities.
Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Time Series Regressions: Global Warming

	Less Exposed			Highly Exposed		
	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
Global Warming	-0.480	0.902	1.426**	9.529**	2.841*	3.534***
	(1.952)	(0.893)	(0.711)	(4.816)	(1.472)	(1.218)
SPX Returns	-1.337***	-0.749***	-0.632***	-2.163***	-1.079***	-0.866***
	(0.295)	(0.146)	(0.120)	(0.398)	(0.162)	(0.132)
MSCI Local Returns	-1.376***	-0.693***	-0.540***	-1.654***	-0.802***	-0.558***
	(0.182)	(0.088)	(0.069)	(0.191)	(0.084)	(0.071)
Exchange Rate Dollar	1.401***	0.838***	0.548**	-0.452	0.010	0.006
	(0.529)	(0.294)	(0.228)	(0.301)	(0.237)	(0.175)
Intl Reserves	-0.173	0.027	0.050	-0.000**	0.000***	0.000***
	(0.144)	(0.069)	(0.093)	(0.000)	(0.000)	(0.000)
5 Yr Treasury	0.124**	0.006	-0.004	0.204**	0.003	-0.018
	(0.048)	(0.022)	(0.018)	(0.082)	(0.031)	(0.023)
VIX	0.028	0.007	0.002	-0.001	-0.022	-0.025
	(0.025)	(0.010)	(0.008)	(0.062)	(0.022)	(0.017)
Observations	6127	6127	6127	1547	1547	1547
R^2	0.133	0.233	0.195	0.167	0.262	0.252

Table 7 presents regressions estimated with equation 3. The regressions are estimated with only country fixed effects to investigate the relationship between the global warming index (Global Warming) and sovereign risk. The Less Exposed panel consist of countries in quintiles four through one in Table 4 whereas the Highly Exposed panel contains the fifth quintile countries. Both global and local financial variables are kept. Each panel reports the regression coefficients of the growth in sovereign CDS spreads in the 1-, 5-, and 10-year maturities.
Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Cross-Sectional Regressions: Google Searches on "Sea Level Rise"

	Less Exposed			Highly Exposed		
	(1) 1 Yr	(2) 5 Yr	(3) 10 Yr	(4) 1 Yr	(5) 5 Yr	(6) 10 Yr
SVI 95th Pctile	-0.362	0.231	-0.382	3.339	1.848*	1.527*
	(1.810)	(0.756)	(0.642)	(2.755)	(1.056)	(0.867)
MSCI Local Returns	-1.517***	-0.640***	-0.487***	-1.272***	-0.551***	-0.321***
	(0.139)	(0.061)	(0.050)	(0.249)	(0.084)	(0.064)
Exchange Rate Dollar	1.022**	0.738***	0.439***	0.078	0.631***	0.527***
	(0.486)	(0.171)	(0.118)	(0.581)	(0.229)	(0.173)
Intl Reserves	0.125	0.166***	0.134***	-0.000***	-0.000	-0.000
	(0.138)	(0.058)	(0.042)	(0.000)	(0.000)	(0.000)
Observations	2595	2595	2595	1428	1428	1428
R^2	0.369	0.519	0.507	0.460	0.564	0.548

Table 8 presents regressions estimated with equation 4. The regressions are estimated with only year by month fixed effects to investigate the relationship of Google searches of the topic "Sea Level Rise". SVI 95th Pctile is a 0/1 indicator variable with 1 representing periods where searches in a country are two standard deviations above the mean. Since the topic is very specific, the index is only available for 34 countries. However, only Egypt is dropped from the top quintile of stock exposed countries and the remaining 22 countries are in the bottom four quintiles. The Less Exposed panel consist of the 22 remaining countries in quintiles four through whereas the Highly Exposed panel contains the fifth quintile countries in Table 4 with the removal of Egypt. The global financial variables, VIX, 5 year Treasury, and the S&P 500 returns are dropped due to the time fixed-effects. Each panel reports the regression coefficients of the growth in sovereign CDS spreads in the 1-, 5-, and 10-year maturities.
Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Historical and Future Sea Level Rise *Trend* Exposure

Panel A			Panel B		
Country	$HTREND$	PValue	Country	$FTREND$	PValue
Norway	0.012	0.328	Malaysia	0.017	0.253
Finland	0.011	0.004	Philippines	0.013	0.362
Thailand	0.010	0.056	Panama	0.009	0.054
Denmark	0.008	0.029	China	0.008	0.491
China	0.007	0.048	Indonesia	0.007	0.024
Republic of Korea	0.004	0.026	Japan	0.007	0.085
Malaysia	0.002	0.093	Spain	0.007	0.096
Croatia	0.002	0.177	Thailand	0.004	0.368
Ireland	0.001	0.106	Portugal	0.002	0.315
Brazil	0.001	0.008	Morocco	0.002	0.175
Sweden	0.001	0.836	Uruguay	0.001	0.673
Russia	0.000	0.527	Ireland	0.000	0.618
Philippines	-0.001	0.683	Ghana	0.000	0.581
Portugal	-0.001	0.372	Republic of Korea	0.000	0.364
France	-0.001	0.581	France	0.000	0.987
Poland	-0.001	0.310	Poland	-0.001	0.848
Germany	-0.002	0.113	Norway	-0.001	0.800
Japan	-0.004	0.564	Lithuania	-0.001	0.796
Egypt	-0.004	0.386	United Kingdom	-0.002	0.850
Lithuania	-0.005	0.000	Denmark	-0.003	0.873
Indonesia	-0.006	0.022	Belgium	-0.004	0.945
Ghana	-0.006	0.052	Finland	-0.004	0.765
United Kingdom	-0.006	0.075	Egypt	-0.004	0.882
Latvia	-0.012	0.003	Germany	-0.004	0.776
Belgium	-0.041	0.100	Latvia	-0.005	0.771

Table 9 presents *trend* exposure for the top two quintiles of *stock* exposure in Table 4. Historical trend exposure ($HTREND$) is measured using the AR(1) model in equation 1 with the point estimates of percent population exposed for each country from 2000 to 2019. $FTREND$ is calculated using future climate and population model data that is used to estimate potential population exposed. The data is available for each decade from 2010 to 2100 and these point estimates are input into equation 1. Panel A and B represents the trend rankings of the countries using the historical and future data, respectively. The p-values of the AR(1) model are presented on the right hand side of each panel.

Table 10. Time Series Regressions: Trend

	HTREND				FTREND			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Improving	Worsening	Improving	Worsening	Improving	Worsening	Improving	Worsening
Adaptation	3.492**	2.684**			3.740***	2.360		
	(1.517)	(1.353)			(1.431)	(1.520)		
Global Warming			3.134**	2.349**			3.219***	1.985*
			(1.244)	(1.165)			(1.248)	(1.202)
SPX Returns	-0.802***	-0.778***	-0.793***	-0.771***	-0.686***	-0.907***	-0.676***	-0.900***
	(0.137)	(0.130)	(0.137)	(0.130)	(0.126)	(0.143)	(0.125)	(0.143)
MSCI Local Returns	-0.694***	-0.618***	-0.676***	-0.610***	-0.561***	-0.795***	-0.545***	-0.785***
	(0.070)	(0.059)	(0.068)	(0.059)	(0.069)	(0.066)	(0.068)	(0.065)
Exchange Rate Dollar	0.043	0.399***	0.036	0.374***	0.057	0.310	0.048	0.298
	(0.200)	(0.133)	(0.200)	(0.133)	(0.168)	(0.199)	(0.168)	(0.199)
Intl Reserves	0.021	0.000***	0.021	0.000***	0.000***	0.106**	0.000***	0.107**
	(0.017)	(0.000)	(0.017)	(0.000)	(0.000)	(0.052)	(0.000)	(0.053)
5 Yr Treasury	0.011	-0.024	-0.002	-0.033	-0.033	0.038	-0.047**	0.030
	(0.022)	(0.024)	(0.022)	(0.025)	(0.023)	(0.024)	(0.023)	(0.024)
VIX	-0.028*	-0.018	-0.026*	-0.016	-0.035**	-0.003	-0.033**	-0.002
	(0.015)	(0.017)	(0.015)	(0.017)	(0.015)	(0.017)	(0.015)	(0.017)
Observations	1533	1428	1533	1428	1533	1428	1533	1428
R^2	0.271	0.321	0.271	0.321	0.226	0.346	0.226	0.346

Table 10 presents regressions estimated with equation 3. The regressions are estimated with only country fixed effects to investigate the relationship between the adaptation, global warming and sovereign risk. The *HTREND* panel divides countries using the trend component calculated for each country with the historical surge exposure data. In contrast, the *FTREND* panel splits countries into groups using the calculated trend component with future exposure data. Improving columns consist countries in the top half of Table 9 whereas worsening columns comprise of countries in the bottom half. The first and second row represent the adaptation and global warming attention indices used, respectively. Both global and local financial variables are kept. Each column reports the regression coefficients of the growth in sovereign CDS spreads for only the 10-year maturity.

Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11. Robustness Check: Protection Against SLR

	(1) 1 Year	(2) 5 Year	(3) 10 Year	(4) 1 Year	(5) 5 Year	(6) 10 Year
Adaptation	4.395	0.248	0.796			
	(9.315)	(2.534)	(1.921)			
Global Warming				1.207	1.017	1.566
				(6.373)	(2.172)	(1.649)
SPX Returns	-1.157	-0.382	-0.398**	-1.129	-0.385	-0.398**
	(1.064)	(0.245)	(0.185)	(1.026)	(0.243)	(0.184)
MSCI Local Returns	-2.618***	-0.969***	-0.723***	-2.614***	-0.964***	-0.716***
	(0.902)	(0.147)	(0.103)	(0.901)	(0.150)	(0.104)
Exchange Rate Dollar	-0.241	0.547	0.275	-0.214	0.530	0.253
	(1.465)	(0.484)	(0.344)	(1.500)	(0.487)	(0.347)
Intl Reserves	-0.863	-0.069	-0.079	-0.859	-0.068	-0.078
	(0.891)	(0.069)	(0.052)	(0.892)	(0.069)	(0.052)
5 Yr Treasury	0.022	-0.036	-0.036	0.015	-0.039	-0.042
	(0.155)	(0.042)	(0.033)	(0.157)	(0.042)	(0.033)
VIX	-0.029	0.005	-0.015	-0.027	0.005	-0.015
	(0.095)	(0.029)	(0.023)	(0.094)	(0.029)	(0.023)
Observations	714	714	714	714	714	714
R^2	0.078	0.221	0.215	0.078	0.222	0.215

Table 11 presents regressions estimated with equation 3. The regressions are estimated with only country fixed effects to investigate the relationship between the adaptation, global warming and sovereign risk. The sample of regions include Hong Kong, Israel, Italy, Quatar, Bahrain, and the Netherlands. The first three columns only include the adaptation index and the last three include the global warming index Both global and local financial variables are kept. Each column reports the regression coefficients of the growth in sovereign CDS spreads in the 1-, 5-, and 10-year maturities.
Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12. Robustness Check: Sovereign CDS Trades & Notional

	Least Exposed				Most Exposed			
	(1) Trades	(2) Notional	(3) Trades	(4) Notional	(5) Trades	(6) Notional	(7) Trades	(8) Notional
Warming	-8.45	-281.38			120.99	353.49		
	(33.87)	(202.62)			(150.55)	(415.33)		
Adaptation			91.45**	-187.35			169.63**	380.15*
			(38.58)	(158.92)			(75.12)	(197.70)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearxMonth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R Sq	0.03	0.00	0.03	0.00	0.04	0.02	0.04	0.02
Obs	6060	6060	6060	6060	2175	2175	2175	2175

Table 12 presents regressions estimated with the weekly growth in gross notional amounts and trades of sovereign CDS contracts as the dependent variable. The less exposed panel contains countries that are the least exposed to *stock* SLR while the highly exposed panel contains only the fifth quartile of exposure as detailed in Table 4. The inclusion of the adaptation and global warming indices are alternated. The regressions are estimated with country and month by year fixed-effects across all columns.
Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

7 Figures

Figure 1. Population of Philippines: Total (Left) and Exposed (Right)

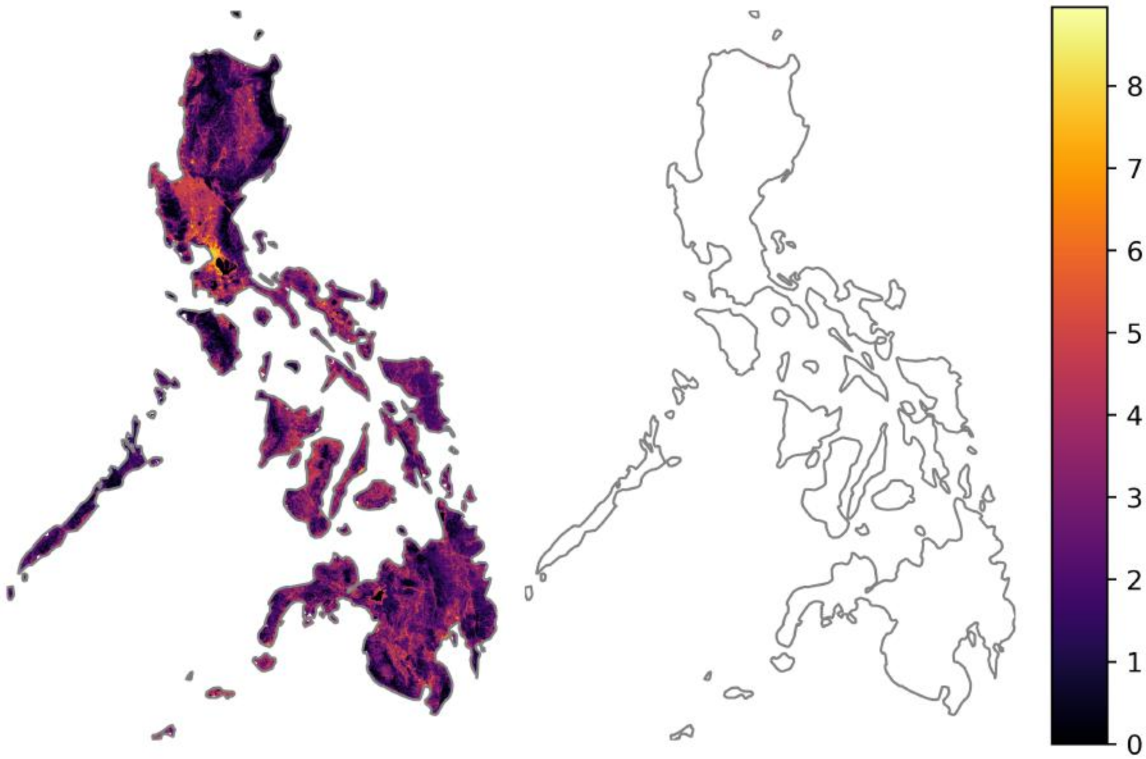

Figure 1 presents a snapshot of the population in the Philippines in 2010. The left hand side presents the total population in log form. The panel on the right illustrates the population exposed to *stock* surge exposure.

Figure 2. Population of Vietnam: Total (Left) and Exposed (Right)

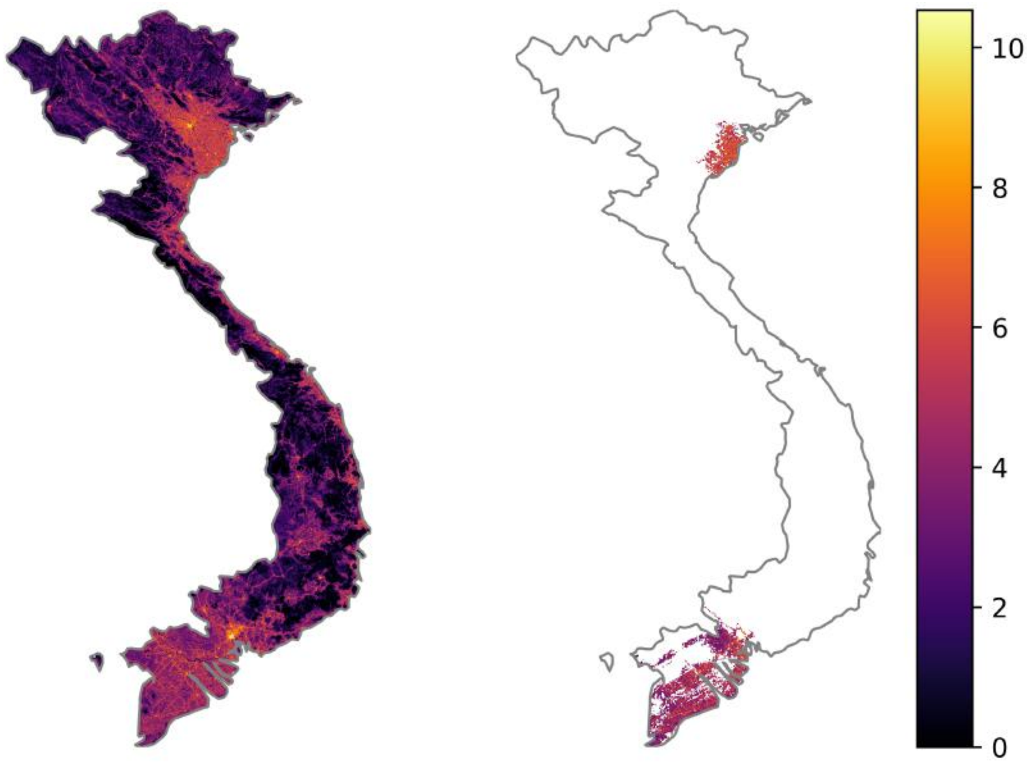

Figure 2 presents a snapshot of the population in the Vietnam in 2010. The left hand side presents the total population in log form. The panel on the right illustrates the population exposed to *stock* surge exposure.

Figure 3. Global Attention Indices

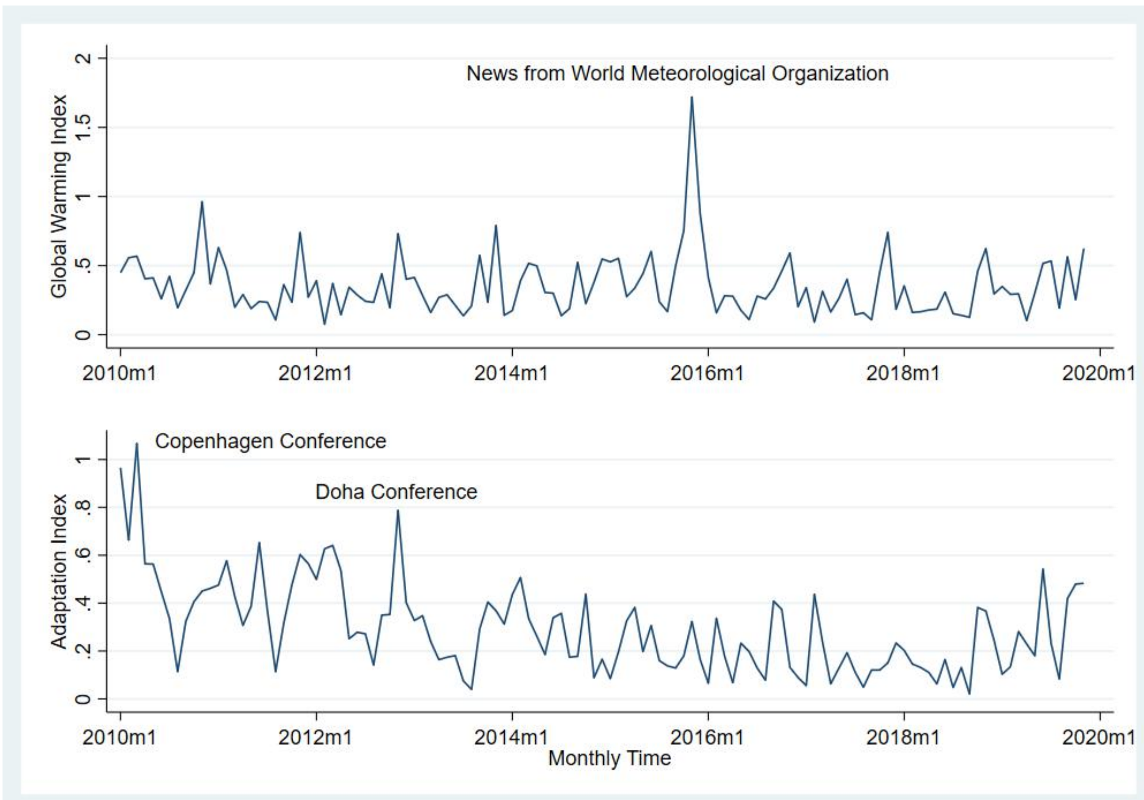

Figure 3 presents a time-series of the global warming and adaptation index from Faccini et al. (2021). Originally, the adaptation index is considered as an international summits index; however, I contend that adaptation is heavily discussed during these summits