Sea Level Rise Exposure and Municipal Bond Yields*

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Abstract

We show that municipal bond markets began pricing sea level rise (SLR) exposure at the end of 2011, coinciding with upward revisions of SLR projections. The effect is present across maturities and is concentrated on the East and Gulf coasts, where storm risk is greatest. We apply a structural model of credit risk to show that municipal bond investors expect a one standard deviation increase in SLR exposure to correspond to a reduction of 3% to 8% in the present value or an increase of 2% to 4% in the volatility of the local government cash flows supporting debt repayment.

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Disclosure Statement for Paul Goldsmith-Pinkham

"Sea Level Rise Exposure and Municipal Bond Yields"

The author declares that he has no relevant or material financial interests that relate to the research described in this paper.

Disclosure Statement for Matthew T. Gustafson

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Over the past two decades, popular interest in climate change has increased dramatically as scientific forecasts have become more dire. A potential byproduct of a warming climate is sea level rise (SLR). Since the 2007 Intergovernmental Panel on Climate Change (IPCC) report, scientists have increased SLR projections fourfold, with current upper-bound projections of 2.5 meters by 2100 (e.g., Stocker et al. (2013); Sweet et al. (2017); DeConto and Pollard (2016)). In addition, scientific reports (e.g., Webster et al. (2005); Holland and Bruyère (2014); Hayhoe et al. (2018)) have drawn attention to more immediate risks for coastal communities, such as increasingly severe tropical storms and the potential for SLR to amplify storm-related flooding. Estimating the economic costs of SLR exposure is important from a policy perspective because these costs represent benefits of climate remediation that can be weighed against the costs of interventions.

In this paper, we examine how exposure to SLR risk is priced in the municipal bond market. Several features of the municipal bond market make it an valuable setting for understanding the potential impact of climate risk on local economies. First, the payoff profile of bonds makes the likelihood of large negative shocks a key driver of prices, which reflect a local government's ability to repay the debt using future cash flows (e.g., tax revenues, intergovernmental transfers, debt issuance). Second, the sources of repayment for municipal bonds are local in nature, especially so for the school district bonds that comprise our sample and are commonly backed by real estate taxes. Finally, the simple payoff structure of municipal bonds and their close connection to local economic conditions provide an opportunity to translate effects on asset prices into more general economic effects of SLR exposure on coastal communities.

Estimating the effect of SLR exposure on the value of municipal bonds and their underlying cash flows is difficult for two reasons. The first challenge is that many factors correlated with SLR exposure (e.g., proximity to the coast) are also correlated with time-varying economic risks. We address this issue by using detailed local variation in school districts' SLR exposure, which allows us to compare bonds from issuers in the same county and traded in the same time period, but varying in within-county, district-level SLR exposure. The second challenge is to translate estimated changes in credit spreads to changes in the local government's cash flow stream backing the bonds. We tackle this problem by adapting a structural model of credit risk from the corporate finance literature to the municipal bond market.

We find that the municipal bond market does not price SLR exposure until the fourth quarter of 2011, after which we observe that bonds with issuers exposed to SLR risk have significantly higher credit spreads than those with unexposed issuers. Strikingly, the evolution of the estimated pricing effect closely tracks the evolution of scientific forecasts and popular interest regarding SLR. In terms of magnitudes, we find that in 2017, the last year of our sample, a ten percentage point (approximately one standard deviation) increase in the number of properties exposed to six feet of sea level rise is accompanied by a 5 basis point increase in municipal bond credit spreads, equivalent to 8% of the average spread in our sample. The estimated effect of SLR exposure is stronger on the East and Gulf coasts, with a ten percentage point increase in exposure corresponding to an increase in credit spreads of between 7 and 9 basis points.[1]

To interpret the economic magnitude of our findings, we adapt the Merton (1974) model of credit risk to the municipal bond market.[2] We use the model to translate the estimated effects of SLR exposure on bond yields into implied changes in the future distribution of local government cash flows. After calibrating the model to match the average yield of municipal bonds in our sample, we find that our estimates for the East and Gulf coasts are consistent with a reduction of 3% to 8% in the present value of the underlying cash flow stream or a proportional increase of 2% to 4% in the volatility of cash flows, depending on the current condition of the issuer's balance sheet. The large economic consequence implied by a small increase in yields is due to the low unconditional risk of municipal bonds. The estimated effects of SLR exposure on bond prices do not imply a large probability of climate-induced default, but they do suggest that investors anticipate a material economic impact of SLR risk on exposed municipalities.

We consider two primary channels through which SLR exposure could be affecting municipal bond prices. First, there is the risk of slowly rising oceans that will eventually inundate coastal properties. We expect this long-run risk to affect all coastal municipalities similarly, conditional on exposure, but to affect only long-maturity bonds. Second, SLR exposure is highly correlated with exposure to tropical storms or hurricanes, which experts project will become more severe as the climate warms (e.g., Webster et al. (2005); Holland and Bruyère (2014); Hayhoe et al. (2018)).

[1]We begin to observe a statistically significant relation between SLR exposure and credit spreads on the East Coast in the second quarter of 2011, slightly before we observe a significant effect in the full sample. This timing suggests that the pricing effects are not a reaction to Hurricane Sandy, which made landfall in October 2012.

[2]Although the Merton (1974) model has trouble matching the observed level of corporate credit spreads (e.g., Huang and Huang (2012)), Schaefer and Strebulaev (2008) show that it provides accurate predictions of the relation between changes in yields and asset values.

SLR projections may also interact with expected storm damages directly as increases in the water table, induced by small amounts of near-term SLR, can increase the damages associated with storm surges and the immediate costs of floods (see Passeri et al. (2018)).

The fact that the SLR exposure premium in the latter part of our sample is concentrated on the East and Gulf coasts, and statistically insignificant on the West coast, supports the second channel. Compared to the East and Gulf coasts, the West coast experiences few storm-related flooding events. Indeed, the NOAA does not even produce storm surge hazard maps for the West coast, but does for the remainder of the country.[3]

To further investigate the channel, we partition the sample of bonds by time to maturity. Again consistent with short-run effects being relevant, we observe statistically significant effects of SLR exposure for both short and long-maturity bonds. However, when comparing short and long-maturity bonds issued by the same school district and traded in the same month, we find that the estimates are increasing in time to maturity. Overall, the evidence is consistent with investors becoming more concerned about the interplay between SLR and flood exposure, including both near- and long-term risks associated with more severe storm surges and flood damages. However, we cannot rule out the possibility that worsening long-run SLR forecasts contribute to the SLR exposure premium.

We also examine how an area's beliefs with respect to climate change affect the extent to which SLR exposure is priced in the municipal bond market. Bernstein et al. (2019) and Baldauf et al. (2020) find beliefs to be an important predictor of how SLR exposure is priced in real estate markets.[4] The post-2011 SLR exposure premium in the East and Gulf coast municipal bond markets is concentrated in states that are more worried about the expected impact of climate change. Thus, heterogeneity in investor beliefs across markets is a significant determinant of how climate risk affects bond prices.

This paper contributes to the emerging literature on the financial implications of climate risk. Environmental risks have been linked to the valuation of firms (e.g., Bansal et al. (2017), Berkman et al. (2019), Hong et al. (2019)) and their cost of capital (e.g., Sharfman and Fernando (2008), Chava

[3]On the East and Gulf coasts, it is difficult to separate storm surge and SLR exposure, as the two measures have a correlation of 0.69. Thus, the best available proxy for storm surge risk is the coast on which a municipality is located.

[4]We measure climate change beliefs at the state level because preferential tax exemption of in-state bonds leads to state-level segmentation of the municipal bond market (Schultz (2012)).

(2014), Delis et al. (2019)), as well as their operating performance (e.g., Barrot and Sauvagnat (2016), Addoum et al. (2020)) and financial policies (e.g., Dessaint and Matray (2017)). With respect to capital supply, research has shown that climate risk affects the allocation of credit by banks (e.g., Cortés and Strahan (2017), Brown et al. (2019)) and the beliefs of institutional investors (Krueger et al. (2020)). Bennett and Wang (2019) find that municipal bond issuance volumes and yields temporarily increase after natural disasters. Baker et al. (2018), Flammer (2020), and Larcker and Watts (2020) study the pricing of "green" bonds issued to fund environmentally friendly projects. Giglio et al. (2014) and Giglio et al. (2018) show that low discount rates should be used to discount the long-run risks of climate change. We contribute to this body of work by showing that the cost of debt financing depends on location-specific exposure to climate risk. This dependence is growing over time and implies that climate risk is expected to incur real economic costs on exposed issuers both in the near-term and over the long-run.

Our findings build on prior work, including Bernstein et al. (2019) and Baldauf et al. (2020), that shows a negative effect of SLR exposure on residential real estate prices. These studies identify the effect of SLR exposure by comparing two properties in close proximity to each other, so they cannot address the question of how SLR exposure affects the broader economy in coastal areas. Moreover, the pricing of real estate may be affected by the risk aversion of buyers who account for idiosyncratic risks when valuing an asset that accounts for a large fraction of their wealth. By examining the pricing of municipal bonds, we are able to shed light on the expected impact of SLR exposure on the economic health of coastal areas as perceived by financial market participants who can diversify away from location-specific flood risk.

An important contribution of this paper is to adapt a structural model of credit risk from the corporate finance literature to interpret the economic magnitude of the estimated effects of SLR exposure on coastal economies. Our model-based approach to evaluating the effects of SLR risk on borrowing costs is straightforward to apply in other situations where economic shocks affect the cost of risky debt issuance and can be used in non-corporate settings in which it may be difficult to observe the issuer's capital structure and the market value of its assets. We argue that theoretical models are a valuable source of discipline in the interpretation of reduced-form estimates, especially in settings where the underlying shock is difficult to quantify in dollar terms.

This structured approach to interpreting the evidence, along with our reduced-form empirical methods that account for time-varying county-level economic conditions, differentiates our work from Painter (2020), who studies a similar research question using data on new bond issues and a different measure of climate risk.[5] The first important difference between our findings and those in Painter (2020) is with respect to magnitude. Painter (2020) estimates a 23.4 bps increase in long-maturity bond yields in response to a one percent increase in climate risk, measured by Hallegatte et al. (2013) as the annual GDP loss due to current and future flooding risks. Our structural model suggests that this 23.4 bps estimate implies substantially more economic damage, on the order of a 20% reduction in annual GDP, relative to the SLR damages cited in Hallegatte et al. (2013). The model also shows that the magnitudes we estimate, which imply a 3% to 8% reduction in the present value of underlying cash flows, are in fact more consistent with a decline in annual GDP of around one percent.

The timing of our estimated effects also differs from Painter (2020). We find an insignificant effect of SLR exposure on municipal bond spreads before 2011 and a positive SLR exposure premium afterwards. This pattern aligns with rising SLR projections and awareness. Painter (2020) finds that municipal bond markets began pricing SLR exposure in 2007, but does not provide year-by-year estimates. In the Internet Appendix, we present a replication analysis using the data from Painter (2020) that reveals his estimated premium is driven primarily by 2009, when even short-term bonds in exposed areas exhibit a yield premium. After the end of the 2007-09 recession, the effects of climate risk on borrowing costs declines in magnitude (and is negative in 2011 and 2012 for long-maturity bonds), with no evidence that the SLR exposure premium has increased over time. Instead, the evolution of these estimates suggests that the yield premium in Painter (2020) is driven in part by variation in local economic conditions rather than changes in investor perceptions of climate risk.

In sum, the policy implications of our estimates are materially different from those in Painter (2020). Our results suggest that interventions to remediate SLR risk can create value for investors and lower borrowing costs for municipalities today, and that these efforts would lead to meaningful economic benefits for exposed communities on the East and Gulf coasts in both the near-term and the long-term. In contrast, the evidence in Painter (2020) suggests that remediation efforts

[5] In contrast to our measurement of SLR exposure at the school district level, Painter (2020) uses a measure of climate risk for 17 major metropolitan areas that does not differentiate among coastal and inland municipalities in the same region (e.g., Galveston, TX is grouped with the Houston metropolitan area).

would only have very long-term effects and that the expected benefits have declined since 2009, in contrast to the evolution of scientific consensus towards larger risks from SLR exposure.

The remainder of the paper is organized as follows. Section 1 surveys the scientific debate on sea level rise and outlines a conceptual framework for our analysis. Section 2 describes the sample of municipal bonds and our identification strategy. Section 3 presents estimates of the effect of sea level rise on bond credit spreads. Section 4 applies a structural model to interpret our empirical estimates. Section 5 concludes.

1 Background and Hypothesis Development

1.1 The Evolution of Sea Level Rise Projections

The extent to which sea level rise exposure represents a material threat to U.S. coastal communities is a hotly debated question among policymakers and politicians. This disagreement among politicians extends to the scientific community, where there is substantial debate regarding how high and fast seas will rise over the next century. It is widely recognized that the 20th century saw seas rise by 1-2 millimeters per year, with some areas such as the eastern U.S. experiencing significantly more SLR than others. Disagreement arises when translating these past trends into future projections. For their 2007 report, the IPCC considered a variety of emissions scenarios and concluded that seas were likely to rise by between 0.18 and 0.59 meters by 2100. Around the same time, Church and White (2006) reported that extrapolating the current rate of SLR acceleration through the year 2100 would result in approximately 0.3 meters of SLR. Since 2007, opinions on end-of-century SLR have diverged substantially, in large part due to the consideration of new environmental factors that substantially increased upper-bound estimates. Many scientists predict negligible SLR this century (e.g., Hansen et al. (2015)), but worst-case scenario SLR projections have been increasing.

To quantify the evolution of SLR projections, we use information provided in Garner et al. (2018) to construct a panel of scientific papers that project global average SLR through 2100. Garner et al. (2018) highlight a total of 73 different reports from which we select a sample of comparable studies. Most studies model their SLR projections based on agreed-upon emissions scenarios, which change in 2012 with the release of Representative Carbon Pathways. To standardize our analysis, before 2012 we examine A2 (high) and B1 (medium) emissions scenarios and, after 2012 we focus on the RCP8.5 (high) and RCP4.5 (medium) scenarios. Since the emissions pathways of A2 are similar to that of RCP8.5, and the emissions pathways of B1 are similar to RCP4.5, focusing on these models provides continuity from before to after the RCP standardization.

We narrow the universe of reports by imposing the following criteria:

1. We require that the study be semi-empirical, probabilistic, or part of the IPCC or NOAA analysis papers. These methods have become the state-of-the-art in the 21st century and allow for a consistent comparison group.

2. We require that the study explores both medium and high emissions scenarios (e.g., A2 and B1 or RCP8.5 and RCP 4.5)

3. The study must have sufficient information to calculate the mean and variance of global average SLR at the end of the century.

4. We exclude any studies that impose explicit constraints on projection variables or use non-standard temperature projections.

We are left with 22 studies released between 2001 and 2017. To track the evolution of SLR projections, we must make assumptions on how long a particular study is considered "relevant." In some cases, researchers update their analysis, so we simply use the latest update. For instance, when the IPCC releases its 2007 report, the 2001 report becomes obsolete. Other reports appear only once in our sample, in which case we assume a report is relevant for five years after the publication date. Finally, we equally weight across studies and scenarios to identify the average prediction and confidence bounds for each year from 2001 to 2017.[6]

Panel A of Figure 1 summarizes the evolution of sea level rise projections over our sample period. There is a noticeable upward trend in SLR projections, with the average forecast moving from less than two feet in 2001 to nearly four feet by 2017. There is a shift in projections beginning

[6]Internet Appendix Table A5 provides details on how we translate the results of each scientific study into a confidence bound for SLR projections. Most studies provide direct estimates of the probability distribution associated with their forecasts that follow an approximately normal distribution, as shown in Figure 5 of Garner et al. (2018). To compare across studies, we assume normality and use the distribution points provided by each study to determine the mean and standard deviation of its SLR forecast.

in 2007, with the best-case (1st percentile) scenario moving up sharply. We find a significant increase in the worst-case scenario forecasts beginning in 2012, when the 99th percentile of sea level rise projections moved from three feet to over four feet by 2013. Around the same time, a number of studies argued that the potential for glacial collapse in Antarctica may be significantly higher than previously thought. By the end of the sample period, the worst-case scenario involves over five feet of global SLR and the dispersion in forecasts is nearly four feet.

Popular interest in sea level rise and climate risk more generally has risen with the evolution of scientific projections. Panel B of Figure 1 plots the trends in Google searches for the terms "sea level rise" (Panel A) and "climate change" (Panel B) from 2004, when data become available, until the end of our sample in 2017. Both panels reveal steadily increasing interest in climate-related search terms over our sample period.

1.2 Hypothesis Development

In this paper, we take a markets-based approach to aggregating opinions regarding these recent updates in SLR expectations. Our analysis focuses on the credit spreads of municipal bonds, equal to the yield-to-maturity minus a benchmark rate, which we define shortly. All else equal, we expect higher SLR exposure to lead to higher municipal bond credit spreads, due to a heightened risk of value-destructive flooding that increases the probability of default through a reduction in property tax revenues and local economic activity. Combined with the increasing projections of scientists and accompanying popular interest, we arrive at our main prediction: SLR exposure has a positive effect on municipal bond credit spreads that is increasing over the sample period. Empirically, we test this prediction against the null hypothesis that SLR exposure does not significantly impact municipal bond prices.

There are several channels through which climate risk could affect the pricing of municipal bonds. First, there is the long-run risk of slowly rising oceans that will eventually inundate coastal properties. Bernstein et al. (2019) provide evidence that this risk is priced in the residential real estate market, while Giglio et al. (2014) and Giglio et al. (2018) show that low discount rates should be used to discount the long-run risks of climate change. An advantage of the current setting is that municipal bonds are issued at a range of maturities, so we can distinguish short-run and long-run risks in the data. This leads to the prediction that SLR exposure affects credit spreads through the long-run risk of rising oceans. Under this hypothesis, effects should appear in long-maturity bonds, but not in short-maturity bonds. In addition, this hypothesis predicts similar yield premia in all coastal areas since century-long increases in global SLR will have similar effects across regions.[7]

Areas that are more exposed to sea level rise may also experience negative shocks in the near-term from more severe storm-related flooding, Since both SLR and storm severity are projected to worsen to the extent that temperatures rise, projections of tropical storm severity and coastal flooding have evolved along with the evolution of scientific forecasts regarding end-of-century sea level rise. For instance, the fourth National Climate Assessment remarks that "the frequency, depth, and extent of tidal flooding are expected to continue to increase in the future, as is the more severe flooding associated with coastal storms, such as hurricanes and nor'easters" (Hayhoe et al. (2018), pg. 74-75). Importantly, the damages from SLR and storm surge exposure are complementary as small amounts of SLR, which may occur in a matter of years as opposed to decades, can exacerbate the damages of a given storm surge through its effect in elevating the water table. This leads to an alternative prediction, that SLR exposure affects credit spreads through the short-run risk of flooding due to more severe storms.

There are two important differences in the empirical predictions of this channel compared to the threat of long-run SLR-related flooding. First, the time horizon of the effect differs. Both hypotheses predict effects for bonds with long maturities, but the near-term flood risk channel also predicts there to be an effect on short maturity bonds. Second, unlike long-run SLR flood risk, which affects all coastal areas similarly, the short-run risk of flooding is most relevant for areas that experience significant storm surges. Although SLR exposure and storm surge exposure are highly correlated within confined geographic areas, there is significant variation in SLR and storm surge exposure across coasts. In particular, the East and Gulf coasts are subject to storm surges and the West cost is not.[8] Thus, a second important difference between the predictions is that while the long-run risk story predicts similar effects across geographical regions, we expect any effects of short-run SLR exposure risk to be more pronounced on the East and Gulf coasts than

[7] There is some regional variation in sea level rise, but the magnitude of this regional variation is on the order of a few millimeters per year. These differences are expected to persist, but are insignificant compared to worst case end of century global SLR projections (see e.g., Piecuch et al. (2018).

[8] An illustration of this distinction is that the NOAA does not produce storm surge hazard maps for the West coast, but does for the remainder of the country. See www.nhc.noaa.gov/nationalsurge/.

on the West coast.[9]

Our third hypothesis involves the role of investor beliefs about climate change. Bernstein et al. (2019) and Baldauf et al. (2020) both find that local beliefs about climate change affect how real estate markets price SLR exposure. It is reasonable to expect that local beliefs will also matter for municipal bond pricing because buyers are often local retail investors, due to the tax advantages of in-state ownership. Therefore, we predict that SLR exposure is priced more in states where residents are more worried about climate change.

2 Sample Construction

Our empirical analysis studies the effect of SLR exposure on school district bond credit spreads. We focus on bonds issued by school districts for three reasons. First, school districts comprise the smallest, most clearly defined geographic areas among the various types of municipality. This allows us to measure SLR exposure precisely and identify the effect on credit spreads while controlling for time-varying local economic conditions at the county level.[10] Second, public education is an important use of municipal bond proceeds, amounting to 30% of new bond issues and 18% of the dollar amount issued by issuers below the state level of government from 2001 to 2017, so we are able to construct a large sample of school district bonds. Third, much of the funding for public schools in the U.S. comes from taxes on local real estate, so there is a direct economic link between school districts' ability to repay debts and the anticipated effects of SLR on property values (Bernstein et al. (2019) and Baldauf et al. (2020)).

Municipal bond yields are drawn from the intersection of the Mergent Municipal Bond Terms and Conditions database and historical transaction price data from the Municipal Securities Rulemaking Board (MSRB). We select school district bonds from these data by screening on primary and secondary education as the use of proceeds. Following past literature (Schwert (2017)), we

[9]This prediction relates to tropical storms, which are one type of natural disaster expected to intensify in a warming climate. Wildfires are another type of disaster with growing risks that are concentrated on the West coast and limited on the East and Gulf coasts. However, fire risk is more prevalent inland than in coastal areas, and should bias us against finding a positive SLR exposure premium.

[10]In the Internet Appendix, we report results based on the universe of municipal bonds. Most non-school issuers (e.g., cities, counties, hospital authorities, utilities) span broad geographic areas, so it is difficult to disentangle SLR risk from local economic conditions. The effect of SLR exposure in this sample is either negative or insignificant, consistent with coastal counties having better economic prospects than inland counties. This highlights the importance of controlling for local economic conditions and the benefits of our focus on smaller geographic areas. We discuss this issue further in Section 3.1.

restrict attention to fixed-coupon tax-exempt bonds that trade at least ten times, to ensure uniformity and a minimum level of liquidity. We exclude trades after a bond's advance refunding date, if applicable, because the bond is risk-free after that point Chalmers (1998). Additionally, we exclude the first three months after issuance and the last year before maturity because these are times when yields are especially noisy (Green et al. (2007)). We do not impose any restriction on the type of bond issued, as the vast majority of school districts issue general obligation bonds. Our results are robust to controlling for bond type across all of our specifications.

We use the Municipal Market Advisors AAA-rated curve ("MMA curve") as a tax-exempt benchmark for the municipal bond credit spread calculation. This curve is reported daily on Bloomberg from 2001 onward, so our sample spans 2001 to 2017. Using the transaction-level data from the MSRB, we construct a monthly panel of volume-weighted yields at the bond level. We compute a bond's credit spread as the difference between its yield-to-maturity and the maturity-matched par yield from the MMA curve on the last date with a trade in each bond-month. Our results are qualitatively similar using unadjusted municipal bond yields.

We then restrict the sample to coastal watershed counties, as defined by the NOAA, in states with an ocean shoreline.[11] Our process to determine the SLR exposure for each school district issuer within coastal counties closely follows Bernstein et al. (2019). First, we identify the location of each residential dwelling in the school district using the real estate assessor and transaction datasets in the Zillow Transaction and Assessment Dataset (ZTRAX). We then determine each property's SLR exposure using the National Oceanic and Atmospheric Administration (NOAA) SLR viewer (Marcy et al. (2011)). Importantly, the NOAA's SLR calculator accounts for the fact that tidal variation and other coastal geographic factors affect the impact of global oceanic volume increases on local SLR.[12]

Figure 2 illustrates our methodology for a portion of Fairfield County in Connecticut. The black dots denote individual residential properties. The green area represents the extent of chronic tidal flooding after three feet of global average sea level rise as predicted by NOAA SLR viewer,

[11]See coast.noaa.gov/htdata/SocioEconomic/NOAA_CoastalCountyDefinitions.pdf.

[12]Murfin and Spiegel (2020) argue that this exposure measure does not account for subsidence and therefore does not accurately capture SLR risk. NOAA acknowledges this in the SLR methodology: "[subsidence] effects are still sufficiently unknown that they may compound or offset each other in unpredictable ways, such that including only some processes may cause greater error than ignoring them." In other words, the NOAA measure is based on more predictable and better understood factors, but may miss less predictable aspects of SLR exposure.

while the light blue area represents the exposure for six feet of SLR. Naturally, the region with six-foot exposure is larger and encompasses the three-foot exposure region. Finally, the red lines delineate school districts in this part of Fairfield County.

To calculate our measure of SLR exposure at the school district level, we identify the number of properties exposed within each bucket of NOAA SLR risk and divide this by the total number of properties in the school district.[13] For example, to calculate the district-level exposure to six feet of SLR, we count all dots within the blue/green area and divide by the total number of dots in a district to obtain the fraction of properties exposed to chronic tidal flooding. Using the state and name of the school district, we link the geographic exposure information to municipal bond issuers.[14] While we can develop an SLR exposure measure for all districts based on geographic information, our sample shrinks after matching with the municipal bond data. Figure 3 displays the aggregated exposure measure for each school district in the municipal bond sample. SLR exposure is highly skewed, even in our sample, which is restricted to coastal counties. Most school districts in our sample do not have any SLR exposed properties. The 75th, 90th, and 95th percentiles of exposure to six feet of SLR are approximately 1%, 10%, and 20%, respectively.

After merging with the data on SLR exposure, the sample consists of 553,689 bond-month observations of 58,620 bonds issued by 1,492 school districts. As a final step to ensure uniformity over the sample period and to facilitate the estimation of panel regressions with county-time fixed effects, which we describe in the next section, we impose a "balanced panel" restriction on our data. Specifically, we require that each county has more than one district and that each district has at least one secondary market bond price observation per year. After applying these restrictions, the sample consists of 306,033 bond-month observations of 30,088 bonds issued by 352 school districts. The Internet Appendix reports the effects of these restrictions on the sample construction and shows that our results are qualitatively similar without the restrictions. There are 18 states in the unrestricted sample but only 11 in the restricted sample. The most notable exclusion is Florida, where school bonds are issued at the county level. Among the states in the sample, representation

[13] In the Internet Appendix, we show similar results using the value instead of the number of exposed properties as our explanatory variable.

[14] The name matching proceeds in multiple steps. First, we clean and make consistent state names and common abbreviations. We then accept all exact matches between district and issuer names. For the remaining issuers, we remove stop words (e.g. "vocational", "technical" and "elementary") and repeat the matching using the shortened names. We match remaining issuers by hand when we deem the names a close enough match and exclude observations we cannot match. Code for linking the school districts and municipal bond issuers is available upon request.

is tilted towards the most populous states, with California, Texas, New York, and New Jersey accounting for 95.7% of bond-month observations. To ensure that the distribution of observation across states is not driving our results, we replicate our main estimates in the Internet Appendix using weighted regressions in which each state is equally represented.

Table 1 summarizes the variables used in our analysis. About 46% of our observations are from districts that will experience at least some chronic inundation after six feet of global average sea level rise. On average, 6% of properties are exposed at the the six-foot level in these districts. The average municipal bond-month observation in our sample has a yield of 3.33%, which is 63 bps over the AAA-rated benchmark curve. It has ten years to maturity, has aged four years since issuance, and has $621,900 of monthly trading volume (conditional on non-zero trade). We find little unconditional difference in these characteristics between the exposed and full sample, except with respect to trading volume. After winsorizing at the 1% level, municipal bond credit spreads range from -24 bps to 243 bps relative to the MMA benchmark. The dispersion in spreads is narrow relative to other credit markets (e.g., corporate bonds) because of the low historical default rate in the municipal bond market.

3 Empirical Results

Our central hypothesis is that SLR exposure has a positive effect on credit spreads that is increasing along with the rising scientific projections and popular awareness over our sample period. To test this hypothesis, we estimate the following regression:

$$\text{Spread}_{bijt} = c_{jt} + c_i + \sum_{y=2001}^{2017} \left[\alpha_y \text{Frac. Exposed}_i + \beta_y \text{Log(Maturity)}\right] + \gamma X_{bijt} + \epsilon_{bijt}, \tag{1}$$

for bond b issued by school district i, located in county j, trading in year-month t. The coefficients of interest are α_y, which reflect the yearly sensitivity of municipal bond spreads to the fraction of properties in district i that would be inundated by a six-foot rise in sea levels.

We mitigate the possibility that SLR exposure relates to unobserved aspects of the area's economy in two ways. First, we include county-year-month fixed effects throughout our analyses, such that we identify the effect of SLR exposure on yields by comparing bonds issued by school districts located in the same county and traded in the same month. Under the sample restrictions described in the previous section, the mean (median) number of districts with bonds trading in a county-year-month is 4.1 (2).

Second, we exploit the fact that SLR projections and awareness have significantly increased over the 2001 to 2017 sample period by focusing on intertemporal variation in the relation between SLR exposure and municipal bond yields. This specification allows us to control for school district fixed effects that absorb any time-invariant differences across the issuers in our sample. To the extent that a relation between SLR exposure and municipal bond yields emerges or increases as SLR projections become more dire and salient, it is unlikely that the relation we observe is driven by omitted factors. Nevertheless, we present our main results with and without district fixed effects because their inclusion changes the interpretation of our coefficients of interest. In particular, when district fixed effects are included the coefficients on the yearly interactions with the fraction of exposed properties are estimated relative to 2001 as a baseline year.

In addition to county-year-month fixed effects, our empirical specifications include controls for the term structure and the illiquidity of municipal bonds. The yearly coefficients β_y allow for a time-varying term structure of credit spreads based on the logarithm of time to maturity. The control variables X_{bijt} include the coupon rate, the number of years since issuance, the logarithm of monthly volume, and the standard deviation of transaction prices at the bond-month level.

3.1 Effect of SLR Exposure on Bond Yields

Table 2 presents estimates of how sea level rise exposure relates to municipal bond credit spreads over our 2001 to 2017 sample period. Figure 1, which shows how SLR scientific projections and awareness evolve over our sample period, provides context for interpreting these estimates. SLR projections and awareness both rise modestly during the first twelve years of our sample period with the average scientific study released between 2001 and 2011 projecting approximately two feet of end-of-century SLR. After 2011, scientific projections increase rapidly, with worst-case projections in 2017 approaching six feet of end-of-century SLR.

Our first hypothesis is that municipal bond markets price the risk of SLR exposure, resulting in higher yields for exposed districts relative to unexposed districts, especially during the latter part of our sample period. Across columns (1) through (3), we incrementally add controls to the specification, including the bond-level controls and year-month fixed effects. These specifications reveal no evidence of a consistent significant relation between SLR exposure and municipal bond credit spreads. However, there are statistically significant negative coefficients in 2001 to 2002 and 2008 to 2010, which are both periods of slow economic growth in the aftermath of the dot-com bubble and the financial crisis, respectively. These estimates suggest that SLR exposure is negatively correlated with local economic conditions, with more exposed issuers in better financial health than less exposed issuers during macroeconomic downturns.[15] This highlights an important limitation of these specifications, which do little to control for time-varying local economic conditions or time invariant district-level characteristics that may differ between exposed and unexposed areas.

In columns (4) and (5), we interact the year-month fixed effects with state and county fixed effects, respectively. Here, we identify the fraction exposed coefficients from differences in the credit spreads of bonds issued by districts in the same state or county, trading in the same month. The identifying variation is from school districts in the same geographic area that differ in SLR exposure. These specifications reduce the severity of the omitted variable bias highlighted above, but the drops in the coefficient estimates during recessions are still statistically significant. When we refine our control for local economic conditions by including county-year-month fixed effects in column (5), a consistent pattern of positive and significant coefficients emerges in the latter part of the sample.

Finally, in column (6) we add district fixed effects, which control for time-invariant issuer attributes, to the specification with county-year-month fixed effects. This regression shows that bond credit spreads are significantly more positively related to SLR exposure since 2012 than at the beginning of our sample period. From 2012 onward, the point estimates range from 29 to 51 and exhibit a generally positive trend from 2011 through 2015 before leveling off. In contrast, the point estimates exhibit no time trend prior to 2011. We focus on this specification for the remainder of our analysis because it mitigates the correlation between SLR exposure and local economic conditions. The fact that this specification estimates effects relative to 2001 does not qualitatively change the interpretation of our estimates since the estimates we obtain in the latter

[15]This negative correlation has the opposite sign of our hypothesis and contrasts with Painter (2020), who finds a positive and significant effect of climate risk exposure beginning in the second half of 2007, at the outset of a recession. Differences in the scope of our exposure measures (i.e., school district versus metropolitan area) may be responsible for the different correlations with underlying economic conditions.

part of our sample are three to four times larger than the 2001 coefficient. Moreover, the fraction exposed coefficient in 2001 is similar to the coefficient estimates for the other early years of our sample period, suggesting that other benchmark periods yield similar results.

The coefficients of approximately 50 on the fraction of exposed properties from 2015 to 2017 imply that a ten percentage point (or approximately 1.1 standard deviation) increase in the number of SLR exposed properties within a school district is accompanied by a 5 bps larger increase in municipal bond credit spreads at the end of our sample period relative to 2001. Column (5) contains similar estimates of between 38 and 44 basis points without the inclusion of districts fixed effects. The estimates in column (5) are not relative to a reference year and thus indicate that SLR exposure emerges as a significant predictor of municipal yield spreads around 2012.

Panel A of Figure 4 provides a visual depiction of the specification in column (6), with quarterly instead of yearly interactions for a more precise view of when the market began to significantly increase the pricing of SLR exposure. The figure shows that the municipal bond market began pricing SLR risk in the fourth quarter of 2011, with the effect of SLR exposure on municipal bond spreads increasing gradually over the rest of the sample period. These patterns are consistent with the rise in scientific forecasts and popular interest in sea level rise over this period.

Our findings differ from the claim in Painter (2020) that the municipal bond market was pricing SLR risk beginning in the second half of 2007. Although we use different data and a different measure of exposure in our analysis, we provide evidence in the Internet Appendix that the effects of SLR risk on yields in the sample of new issues from Painter (2020) are concentrated around the financial crisis and either negative or statistically insignificant in each year from 2010 to 2016, which indicates the potential for omitted variable bias.

In the Internet Appendix, we provide a number of robustness checks for our main regression. First, we confirm that the representation of states in our sample does not drive the results. Our regression coefficients are qualitatively similar after weighting the regression so that each of the 11 coastal states in our sample are equally represented. Second, our estimates are robust to controlling for local house prices and distance to the coast. Finally, we show that the estimates are qualitatively similar if we measure SLR exposure as the fraction of exposed property value (as opposed to the number of exposed properties) or if we measure exposure to two feet or four feet instead of six feet of global sea level rise.

3.2 Evidence on the Economic Mechanism

The emergence of SLR exposure as a determinant of municipal bond spreads in accordance with recent increases in SLR projections and awareness suggests that municipal bond investors view SLR exposure as related to newly perceived risks. Given our controls for time-varying local economic conditions and the emergence of an SLR exposure premium only in recent years, it is unlikely that this relation is due primarily to unobserved differences between exposed and unexposed districts. Yet, the precise mechanism through which SLR exposure affects municipal bond spreads is unclear.

In this section we examine heterogeneity in the relation between SLR exposure and municipal bond spreads to better understand the underlying mechanism. We first consider the empirical predictions of our second hypothesis, which is motivated by the possibility that the SLR exposure premium is due to long-run risks. To the extent that this is the driving mechanism, we expect the SLR exposure premium to manifest in all geographical regions and to be present only in long-maturity bonds. Alternatively, the SLR exposure premium may be due to investors updating their beliefs on the expected damage from severe storms. Such an effect would also be consistent with the emerging scientific literature (e.g., Webster et al. (2005); Holland and Bruyère (2014); Hayhoe et al. (2018)) that suggests more severe storms are a likely byproduct of a warmer climate. This line of reasoning implies that the SLR exposure premium should be (1) concentrated on the East and Gulf coasts, where storms are more prevalent, and (2) present in both short and long-maturity bonds.

In Table 3, we investigate the extent to which the effect of SLR on bond spreads varies across geographic regions. Columns (1) and (2) restrict the sample to the 55% of our observations that are on the East and Gulf coasts, while columns (3) and (4) restrict the sample to the remaining West coast observations. Columns (1) and (3) replicate the analysis in Column (5) of Table 2 in each subsample. Together, these columns show that the full sample result is driven by the East and Gulf coasts. In column (1), there is no evidence of a significant difference between the exposed and unexposed East and Gulf coast districts prior to 2011. After 2011, a the difference in spreads between exposed and unexposed areas becomes significantly larger, with magnitudes that are approximately twice those observed in the full sample regressions. In contrast, column (3) shows no evidence of a consistent relation between SLR exposure and municipal bond spreads on the West coast at any point in our sample period.

Panel B of Figure 4 plots the coefficient on the East and Gulf coast subsample over our sample period. This illustration shows that the difference between exposed and unexposed districts' spreads was relatively constant prior to 2011. Since that time there has been a significant increase in the relative spreads of exposed districts, peaking in 2015 and remaining significantly positive through the end of our sample period. The largest coefficients of approximately 100 suggest that a ten percentage point increase in the number of SLR exposed properties in a school district is accompanied by a 10 bps larger increase in municipal bond credit spreads in the latter years of our sample, compared to 2001.

In columns (2) and (4) we concentrate the sample on the intensive margin by restricting the analysis to districts with some SLR exposed properties. This ensures that our results are not driven by the use of districts with no exposure as a control group and is particularly relevant for the West coast, where counties are significantly larger than on the East Coast. Dropping unexposed areas decreases the East/Gulf and West coast samples by approximately 35% and 55%, respectively. The results in columns (2) and (4) are very similar to those in columns (1) and (3), suggesting that variation along the extensive and intensive margins produce similar estimates of the effect of SLR risk on municipal bond spreads over our sample period.

The patterns in Table 3 and Panel B of Figure 4 support the hypothesis that the SLR exposure premium is due to investors' changing beliefs regarding the expected damages of future severe storms. To examine this idea further, we separately examine the effect of SLR exposure on short and long-maturity bonds, which are both expected to reflect SLR risk under this hypothesis. In contrast, hypotheses relating to long-run SLR risks predict the SLR exposure premium to be concentrated in long maturity bonds.

To parsimoniously examine how the SLR exposure premium varies by bond maturity, we restrict the sample to the East and Gulf coasts and create a Post indicator that equals one for observations in 2012 and later. Column (1) of Table 4 focuses on the approximately 57% of our observations with less than ten years to maturity, while Column (2) focuses on the long-maturity bonds. Both columns indicate a more positive effect of SLR exposure on bond spreads in the latter part of our sample period. Interestingly, the coefficient is larger for the short-maturity subsample.

This result is inconsistent with both of our hypotheses, but could be due to differences in the types of municipalities issuing long- and short-maturity bonds.

To more closely examine how the SLR exposure premium varies by bond maturity, we use the full range of maturities and introduce a triple interaction between SLR exposure, the 2012-2017 period, and the logarithm of time to maturity. Column (4) adds district-year-month fixed effects to the specification in column (3), such that we compare two bonds with different maturities, issued by the same school district and traded in the same month. Using this approach, we find a positive and significant triple interaction, suggesting that the yield spread on long-maturity bonds is more positively related to SLR exposure later in our sample period. Notably, this result is consistent with both of our empirical predictions. In particular, our prediction motivated by interplay between SLR and storm damages is supported by Columns (1), (2), and (4). There is a significant effect on short-term bonds, but all else equal the SLR exposure premium is larger in the longer-run. This is expected because SLR and storm severity are projected to increase as the climate warms.

Figure 5 more precisely examines when the market began to price SLR exposure for short and long-maturity bonds by plotting the year-by-year estimates for the relation between SLR exposure and municipal bond spreads on the East and Gulf coasts. In both the short and long-maturity subsamples a significantly positive SLR exposure premium emerges in 2012. Although the point estimates are larger for long-maturity bonds for every year after 2010, the point estimates are never significantly different from those in the short-maturity sample. The presence of an SLR exposure premium in both the short and long-maturity samples supports the notion that investors price SLR exposure because it reflects exposure to more severe storms in the immediate and distant future. We find less support for an impact of long-run sea level rise on yields.

In the Internet Appendix, we consider the possibility that the SLR exposure premium is in part due to the effect of long-run SLR risk on real estate prices ((Bernstein et al., 2019)), which leads to an immediate deterioration in the tax base of municipalities. We find little evidence for this channel, as the regression estimates are quantitatively similar after controlling for the average home price in each school district. Nevertheless, we cannot rule out the possibility that part of the SLR exposure premium is due to reductions in property values.

Finally, we examine the role of investors' perception of climate change. Bernstein et al. (2019)

and Baldauf et al. (2020) find that climate change beliefs affect how real estate markets price SLR exposure. It is reasonable to expect that local beliefs will also matter for municipal bond pricing because buyers are often local retail investors, due to the tax advantages of in-state ownership. To measure an area's beliefs about climate change we merge our data with the Yale Climate Opinions map data (Howe et al. (2015)). Specifically, we aggregate 2014 county-level survey data on responses to the question "worried about global warming" to the state level, weighting each county by the number of school districts it houses. We aggregate to the state level instead of using the county-level data directly because the segmentation of municipal bond investors is driven by state-level tax policy. To form our State Worry measure, we then subtract the average state's level of worry and divide by the standard deviation, resulting in a standardized measure that ranges from -2.39 to 0.87.[16]

In columns (1) and (2) of Table 5 we partition the East and Gulf sample based on whether a state's worry about climate change is above or below the median. Above-median states include (from most to least worried) New York, Massachusetts, New Jersey, Rhode Island, Connecticut, and Maine, while below-median states include Texas, South Carolina, Mississippi, and Louisiana. The SLR exposure premium since 2012 is larger and more statistically significant in states with an above-median level of worry. In less worried states, the SLR exposure premium still increases in the later part of our sample. However, this increase is only significant at the 10% level and the coefficient is only approximately 20% of the magnitude as the analogous coefficient in the worried subsample. In column (3) of Table 5 we examine whether the differential effect of SLR exposure is significantly different in worried states in the latter part of our sample by augmenting the specification from equation (1) to include a triple interaction between SLR exposure, the 2012-2017 period, and the state's level of worry about climate change. Consistent with columns (1) and (2), we find that the post-2012 SLR exposure premium is significantly larger in worried states relative to less worried states.

Figure 6 plots the year-by-year estimates for the relation between SLR exposure and municipal bond spreads on the East and Gulf coasts, partitioned by whether the state has an above or below median level of worry about climate change. The blue triangle markers represent the state

[16] In unreported analysis, we find that an area's beliefs regarding the expected impact of climate change are negatively correlated with an area's projected level of SLR.

with above median levels of worry. These estimates are similar to those we obtain in Panel B of Figure 4 using the entire East and Gulf sample. The SLR exposure premium becomes positive and statistically significant in 2012 and becomes increasingly positive throughout most of the remainder of the sample period. Point estimates rise to just over 10 bps for a ten percentage point increase in SLR exposure in 2016. In contrast, the red circle markers reveal no such pattern among less worried states.

Taken together, the evidence in this section suggests that SLR exposure has become a significant positive predictor of municipal bond yield spreads since 2012. Consistent with the SLR exposure premium being due to increasingly dire climate change projections, it emerges at the same time as scientific studies project more significant future SLR. However, our findings suggest that the most likely mechanism through which these increased SLR projections are affecting municipal bond yields is through their effect on investors' expectations regarding the impact of more immediate storm-related events on SLR exposed areas. In particular, our evidence is consistent with investors pricing in the expected damages to exposed areas that accompany the increased probability of severe weather events, which are predicted to become more common and have more severe consequences as seas rise. We also show that local beliefs regarding future climate change is a complementary mechanism through which increased SLR exposure has begun to affect municipal bond spreads. States whose residents report to worry more about climate change drive the yield premium for SLR exposed areas.

4 Interpretation of Magnitudes

4.1 Structural Model of Municipal Credit Risk

The estimates presented in the previous section reveal a statistically significant effect of SLR exposure on municipal borrowing costs. We estimate that a ten percentage point increase in the number of properties in a school district that are exposed to six feet of global average sea level rise is associated with an increase in credit spreads of between 5 and 10 basis points, depending on the regression specification and the sample of bonds. Interpreting the credit spread as the risk-neutral expected loss rate (Duffie and Singleton (1999)), the estimated effect implies a small increase in the default probability of exposed issuers relative to unexposed issuers.

However, the unconditional probability of default in the municipal bond market is very low, so small increases in credit spreads could correspond to material changes in the underlying fundamentals. In this section, we use a simple structural model of credit risk based on Merton (1974) to provide economic context for the magnitude of our estimates. The model allows us to quantify the expected impact of shocks to the present value and volatility of municipal cash flows on the yields of municipal bonds.

Before proceeding, we should provide some context for this exercise. First, structural models of credit risk have not been applied to the municipal bond market, so we are careful to map the model parameters into analogous economic primitives in the public finance context. Second, the failure of structural models to match the observed yields of corporate bonds has been well documented (e.g., Huang and Huang (2012)). We anticipate that these models would exhibit the same shortcomings in this setting. However, our objective is not to match municipal bond yields, but rather to predict changes in yield as a function of changes in the present value of the cash flow stream backing the bonds. We find support for this exercise in Schaefer and Strebulaev (2008), who show that the Merton (1974) model provides very accurate predictions of the empirical hedge ratios of corporate bonds, including high-investment-grade (e.g., AA-rated) bonds that have similar default risk to municipal bonds.

In the Merton (1974) model, the market value of a firm follows a geometric Brownian motion under the risk-neutral measure,

$$d \ln V_t = \left(r - \frac{1}{2}\sigma^2 \right) dt + \sigma dW_t^Q. \tag{2}$$

In the municipal context, the bond issuer is a local government with the power to tax rather than a firm with productive assets, but the interpretation of the model is very similar to the corporate context. The source of debt repayment is a stream of cash flows from tax revenues and intergovernmental transfers. The present value of these cash flows, which we refer to as the asset value, is equivalent to the market value of a firm in the standard discounted cash flow framework.[17]

[17] If the issuer were to default, bondholders would have a claim on the future stream of revenues and would recover an amount determined in a Chapter 9 bankruptcy proceeding. From the perspective of creditors, the main difference between municipal and corporate bankruptcy is that asset liquidation cannot be forced by creditors under Chapter 9. However, the assets of a firm derive their value from the ability to generate cash flows, so this distinction is really about managerial agency and corporate control, which are outside of the model.

Assume that the municipality has a zero-coupon bond issue outstanding with face value K that matures at time T. The payoff to the bond is equivalent to a portfolio containing a risk-free bond and a short put option on the value of assets struck at the bond's face value. Under this basic setup, the value of the bond is

$$B = V - \left[V\Phi(d_1) - Ke^{-rT}\Phi(d_2) \right], \tag{3}$$

where

$$d_1 = \frac{\ln\left(V/K\right) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}, \quad d_2 = d_1 - \sigma\sqrt{T}. \tag{4}$$

The bond's yield-to-maturity can be expressed as $y = \frac{1}{T}\ln\left(K/B\right)$ because it is modeled as a zero-coupon security. Most municipal bonds pay coupons that are exempt from income taxation, so we use a tax-exempt risk-free rate for our calibration. We compute a bond's credit spread as the difference between its yield and the risk-free rate. Throughout this discussion, we use yield and credit spread interchangeably, as we are holding the risk-free rate fixed in our analysis.[18]

We consider two modifications to the model for robustness. First, we incorporate a bankruptcy cost that reduces the asset value proportionally by a factor in the event of default. The infrequency of municipal default makes it difficult to assess what level of bankruptcy costs is appropriate, so we show robustness to alternative specifications. Second, we consider the possibility that the issuer has outstanding debt that ranks senior to its municipal bonds. For instance, Ivanov and Zimmermann (2019) document that bank loans are becoming a more prominent source of funding for municipalities. There are no public data on municipal debt structure, so again we show robustness to alternative specifications to address this issue.

The extended model with bankruptcy costs and two classes of debt follows Schwert (2020). The municipality has a senior loan with face value K_S and a junior bond with face value K_J, both maturing at time T. The payoff to the bond is equivalent to a portfolio containing a long call option struck at the face value of senior debt and a short call option struck at the sum of total face value

[18]The credit risk framework considered here is usually applied to taxable corporate bond yields. Our calculation of the model parameters implied by municipal bond yields accounts for the tax exemption's effect on the pricing of credit risk. In the Internet Appendix, we obtain quantitatively similar estimates performing the model analysis on tax-adjusted yields as in Schwert (2017), using the LIBOR interest rate swap curve as the risk-free benchmark.

of debt. Under this setup, the value of the bond is

$$B_\alpha = (1-\alpha)\left[V\left(\Phi(d_{1,S}) - \Phi(d_1)\right) - K_S e^{-rT}\left(\Phi(d_{2,S}) - \Phi(d_2)\right)\right] + K_J e^{-rT}\Phi(d_2), \tag{5}$$

where

$$d_{1,S} = \frac{\ln\left(\frac{V}{\min\{K_S/(1-\alpha), K_S+K_J\}}\right) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}, \quad d_{2,S} = d_{1,S} - \sigma\sqrt{T} \tag{6}$$

and d_1 and d_2 are defined as in equation (4).

4.2 Model Calibration and Predictions

Our objective is to estimate the yield change for a typical municipal bond following a shock to the distribution of the issuer's cash flows. Table 1 indicates that the mean bond in our sample has a yield-to-maturity of 3.33%, which corresponds to a credit spread of 63 bps over the maturity-matched AAA-rated tax-exempt benchmark rate of 2.70%. The average bond has ten years to maturity, which corresponds to a duration of 7.5 years that we use to calibrate the maturity of the zero-coupon bond in the model. Thus, we set $T = 7.5$, $r = 2.70\%$, and $y = 3.33\%$ for our calibration. We consider other specifications to shed light on the robustness of our predictions and to relate our estimates to the magnitudes in Painter (2020).

Data on the capital structure and cash flows of municipal issuers are difficult to obtain, and it is impossible to measure the market value of the expected cash flow stream. Therefore, we take a flexible approach, calibrating the model to a range of leverage ratios (K/V in the model) and asset volatilities (σ) to match the typical bond yield in the data. To obtain an appropriate set of leverage and volatility pairs, we back out the model-implied asset volatility for leverage ratios ranging from 1% to 99%. Figure 7 shows that the implied volatility is decreasing in leverage, which is intuitive given that we are holding yield-to-maturity fixed in the calibration.

We use these parameter values to compute the model-implied effects of adverse changes in the present value of cash flows (i.e., the underlying asset value) or the volatility of the underlying asset value on the yield-to-maturity of a municipal bond. Figure 8 presents the results of this exercise for proportional changes ranging from 0% to 25%. Overall, the predictions are intuitive and indicate that yield changes are increasing in the magnitude of shocks.

Based on a leverage ratio of 10%, which corresponds to strong current financial standing but a high implied volatility of cash flows, a 1% drop in asset value corresponds to an increase in yield of 1.0 bps, while a 10% drop in asset value raises yields by 10.8 bps. Under the same specification, increases in volatility of 1% and 10% correspond to yield increases of 3.6 bps and 41 bps, respectively. Based on a leverage ratio of 70%, which represents impending financial distress and is associated with the largest yield effects, reductions in asset value of 1% and 10% correspond to yield increases of 2.3 bps and 27 bps, respectively, while increases in volatility of 1% and 10% correspond to yield increases of 2.0 bps and 21 bps.

Table 6 reports similar estimates based on alternative specifications of the model including bankruptcy costs or senior debt, which suggests that our conclusions are robust to the model specification and the possible presence of bank loans on the issuer's balance sheet. In general, large shocks to the underlying cash flow stream are necessary to generate non-trivial increases in yield, given the low level of credit risk in this market.

We can also use the model to shed light on the effects reported by Painter (2020), who finds that a one percent increase in climate risk, measured by Hallegatte et al. (2013) as the annual loss of GDP from sea level rise, corresponds to a 23.4 basis point increase in annualized issuance costs for bond issues with a maximum maturity of 25 years or longer. For this analysis, we use a sample of new issue municipal bonds from Mergent following the data construction in Painter (2020).[19] The average yield-to-maturity of bonds with 25 years or more to maturity is 4.70% in that sample, not far from the 4.58% average issuance yield reported in Table 2 of Painter (2020). The average maturity of these bonds is 30 years, which corresponds to duration of 22.5 years, and the maturity-matched AAA-rated tax-exempt benchmark rate is 4.00%. We also consider the 90th percentile credit spread, which is 181 bps over that benchmark rate, because Painter (2020) finds the strongest effects in ex ante riskier bonds.

The right two columns of Table 6 use these parameters to predict the change in yield resulting from shocks to the value or volatility of the underlying cash flows. For the typical bond, we find that a 1% drop in the underlying asset value, which is equivalent to a 1% drop in annual GDP under the assumption that tax receipts as a fraction of GDP are held fixed, corresponds to only a 0.7 bps increase in yield-to-maturity. The model implies that a drop in annual GDP of about 20%

[19]Marcus Painter generously provided us with replication data for his paper, but the data do not contain offering dates, so we cannot match them to the risk-free rates needed for the model calculations.

is necessary to cause a yield increase of more than 20 bps, even for bonds in the 90th percentile of the credit spread distribution. Intuitively, the implied shock to volatility is smaller, with a 10% proportional increase generating a yield increase of 28 bps for the typical long-maturity bond. We conclude that the estimates in Painter (2020) imply an economic impact that is an order of magnitude larger than the reduction in annual GDP used as his measure climate risk.

4.3 Discussion

What does the model imply about the economic magnitudes from our analysis of municipal bond credit spreads? We estimate that a ten percentage point increase in the number of properties exposed to six feet of sea level rise corresponds to a 8 bps increase in credit spreads for school districts on the East and Gulf coasts. Under the baseline model calibration, this effect is in line with a reduction of 3% to 8% in the present value of the underlying cash flow stream or a proportional increase of 2% to 4% in the volatility of cash flows, depending on the issuer's leverage and corresponding baseline volatility. Although the estimated effects of SLR exposure on bond prices do not imply a large probability of climate-induced default, they do suggest that the municipal bond market is pricing a material economic impact of SLR risk on exposed issuers.

The effect of SLR exposure on the present value of cash flows could be driven by changes in expected cash flows or by movements in discount rates. On its own, the model cannot distinguish between these channels, but there are reasons to believe that our estimates reflect changes in expected cash flows rather than changes in discount rates. Recall that the estimated effect on bond prices is from a difference-in-differences regression framework in which we compare the credit spreads of exposed and unexposed issuers in the same county. Additionally, the marginal investor in the municipal bond is likely to be diversified against any idiosyncratic SLR risk. Thus, any systematic risk needs to have increased differentially for exposed issuers relative to the start of the sample for discount rates to explain our findings. Nevertheless, we urge caution in interpreting the output of our model as exclusively driven by changes in cash flows.

In light of recent events, bailouts by higher levels of government and the funding status of public pensions are important to consider when interpreting our estimates. We acknowledge the likelihood that state governments would increase transfers to affected local governments after the realization of an adverse climate-related shock. If anything, this should attenuate our estimates by reducing the expected impact of climate risk on the financial health of exposed issuers relative to unexposed issuers.

With regard to pensions, most states fund teachers' retirement plans at the state level, so it is unlikely that pension funding has a differential effect on SLR exposed and unexposed school districts in the same county. If pension funding were directly affecting our estimates, then we would expect to see large effects during the financial crisis (Novy-Marx and Rauh (2012)), which we do not. Nevertheless, there is a risk that underfunded pensions reduce the likelihood of intergovernmental transfers conditional on a local shock, which would reduce the attenuation bias from bailouts discussed above.

5 Conclusion

This paper uses the municipal bond market to study the extent to which the risk of sea level rise is priced in financial markets. In line with the evolution of scientific consensus and popular concern about this risk, we find that the market does not price SLR exposure until the fourth quarter of 2011, after which we observe that exposed issuers have significantly higher borrowing costs than unexposed issuers. The effects of SLR exposure on municipal bond prices are concentrated on the East and Gulf coasts, where a one standard deviation increase in SLR exposure corresponds to an 8 bps increase in credit spreads, but no effect on the West coast. We find significant effects for both short and long-maturity bonds.

The patterns we uncover suggest that investors are concerned about how SLR exposure impacts the near-term risk of flooding from storm surges, either via the extensive margin of storms becoming more severe as the climate warms or the intensive margin of SLR amplifying the effects of storm surges due to the elevated water table. Investor beliefs also play an important role in this setting, with the price effects of SLR risk concentrated in states with above-median popular concern about climate risk.

In addition to addressing the question of how climate risk impacts asset prices, an important contribution of this paper is to adapt a structural model of credit risk from the corporate finance literature to interpret the economic magnitude of the estimated effects of SLR exposure. We find that the increase in default probability attributable to SLR risk is low, but that the economic impact is non-trivial, equivalent to a reduction of 3% to 8% in the present value of local government cash flows or a proportional increase of 2% to 4% in the volatility of these cash flows. These estimates shed light on the value that could be unlocked by climate remediation efforts in coastal communities.

We argue that it is important for researchers to discipline their reduced-form findings with a model-based interpretation to avoid misinterpreting the evidence when studying policy-relevant questions such as the financial impact of climate change. Our methodology can be applied in other situations to interpret the effects of economic shocks on risky debt prices, even in settings where it is difficult to observe the issuer's capital structure and the market value of its assets.

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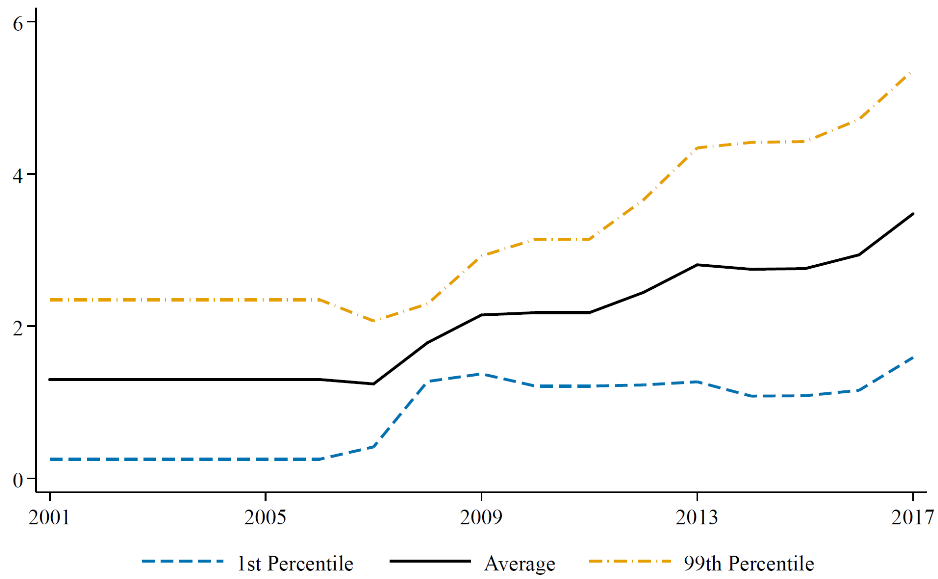
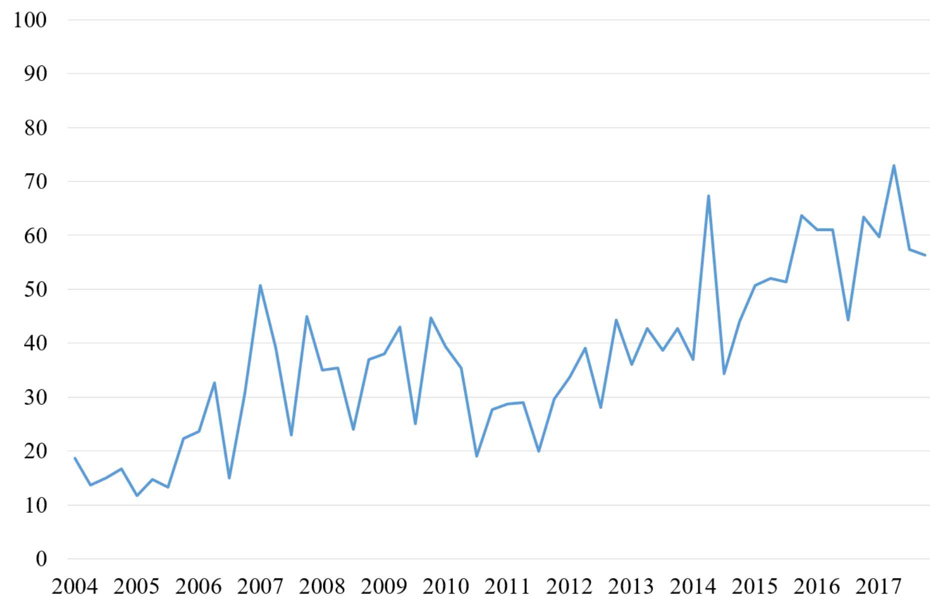
Figure 1: Time Series of Sea Level Rise Projections and Search Trends

Panel A: Scientific Projections of Sea Level Rise

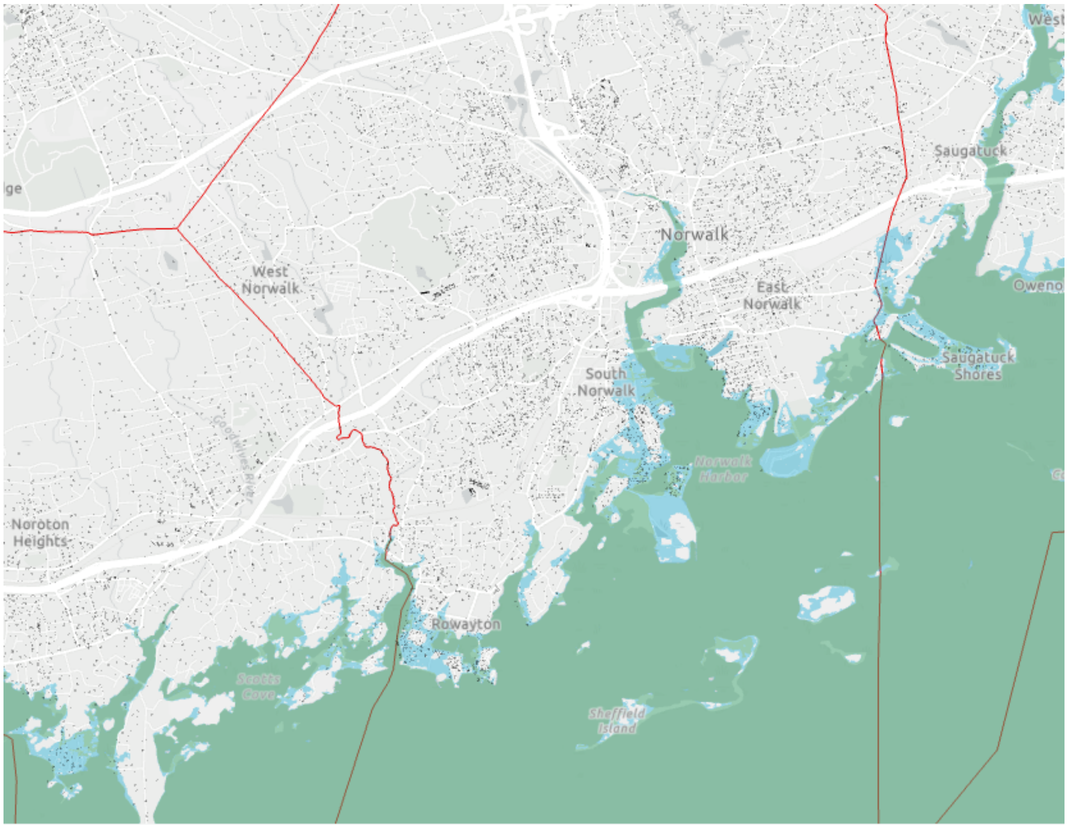


Panel B: Google Search Trends



Note: This figure reports evidence on the evolution of sea level rise (SLR) forecasts and popular interest in SLR over our sample period. Panel A aggregates the mean, 1st and 99th percentiles of SLR forecasts across major scientific studies from 2001 to 2017. Our method for aggregating forecasts is described in Section 1.1 and the list of studies is provided in the Internet Appendix. Panel B plots Google search trends for the term "sea level rise." These data are available on a monthly basis from `trends.google.com` and range from 0 to 100 based on the level of search activity, with the most active month in the sample period scaled to 100. We average the monthly data over each calendar quarter to smooth out high-frequency fluctuations in the series.

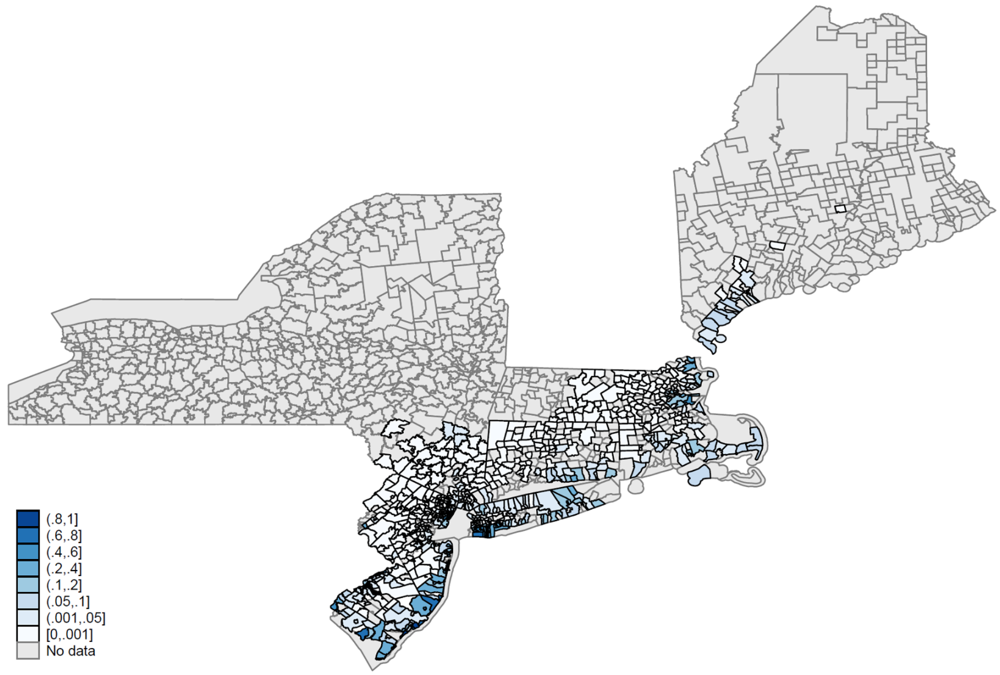
Figure 2: Sea Level Rise Exposure in Fairfield County, Connecticut



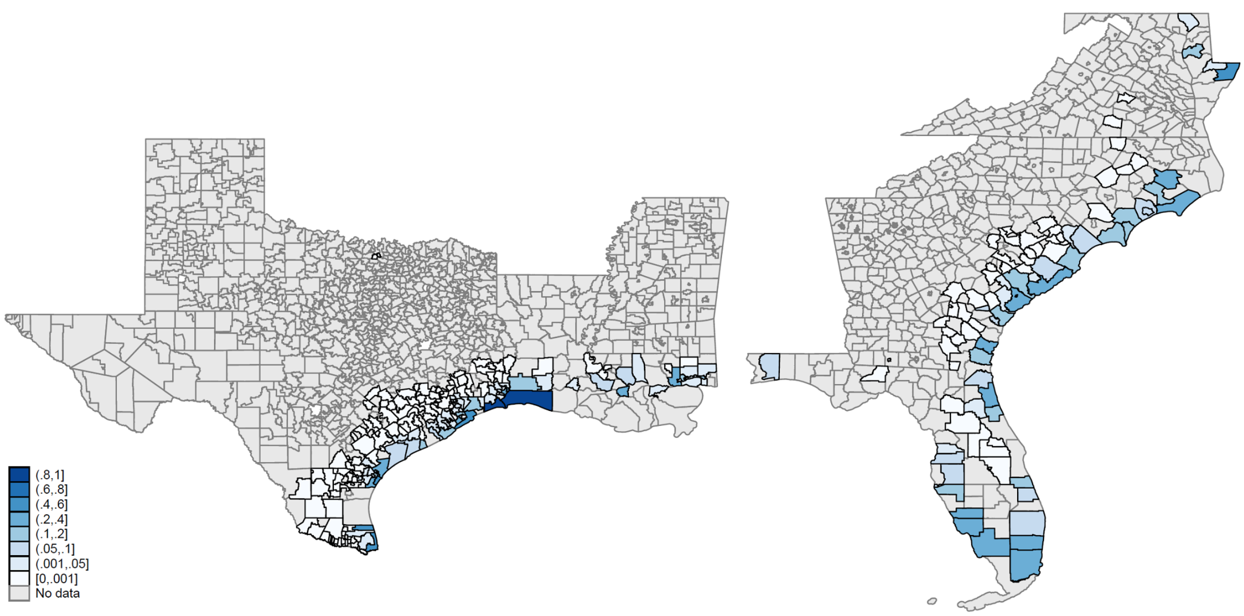
Note: This figure maps housing locations and exposure to sea level rise for a portion of Fairfield County, Connecticut. Black dots are residential dwelling units, the green area is the three-foot NOAA SLR scenario, the light blue area is the six-foot scenario, and the red lines delineate school districts.

Figure 3: School District Exposure to Six Feet of Global Average Sea Level Rise

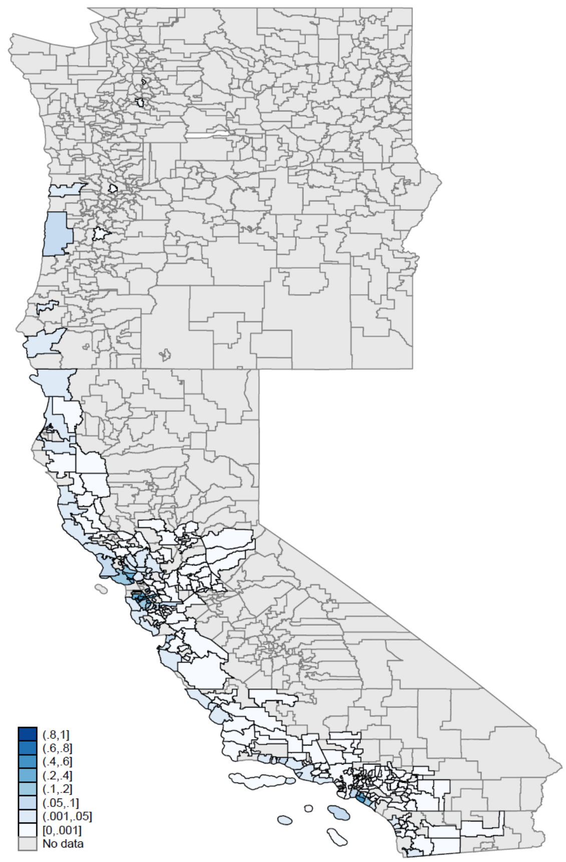
Panel A: Northeast



Panel B: Southeast and Gulf Coast

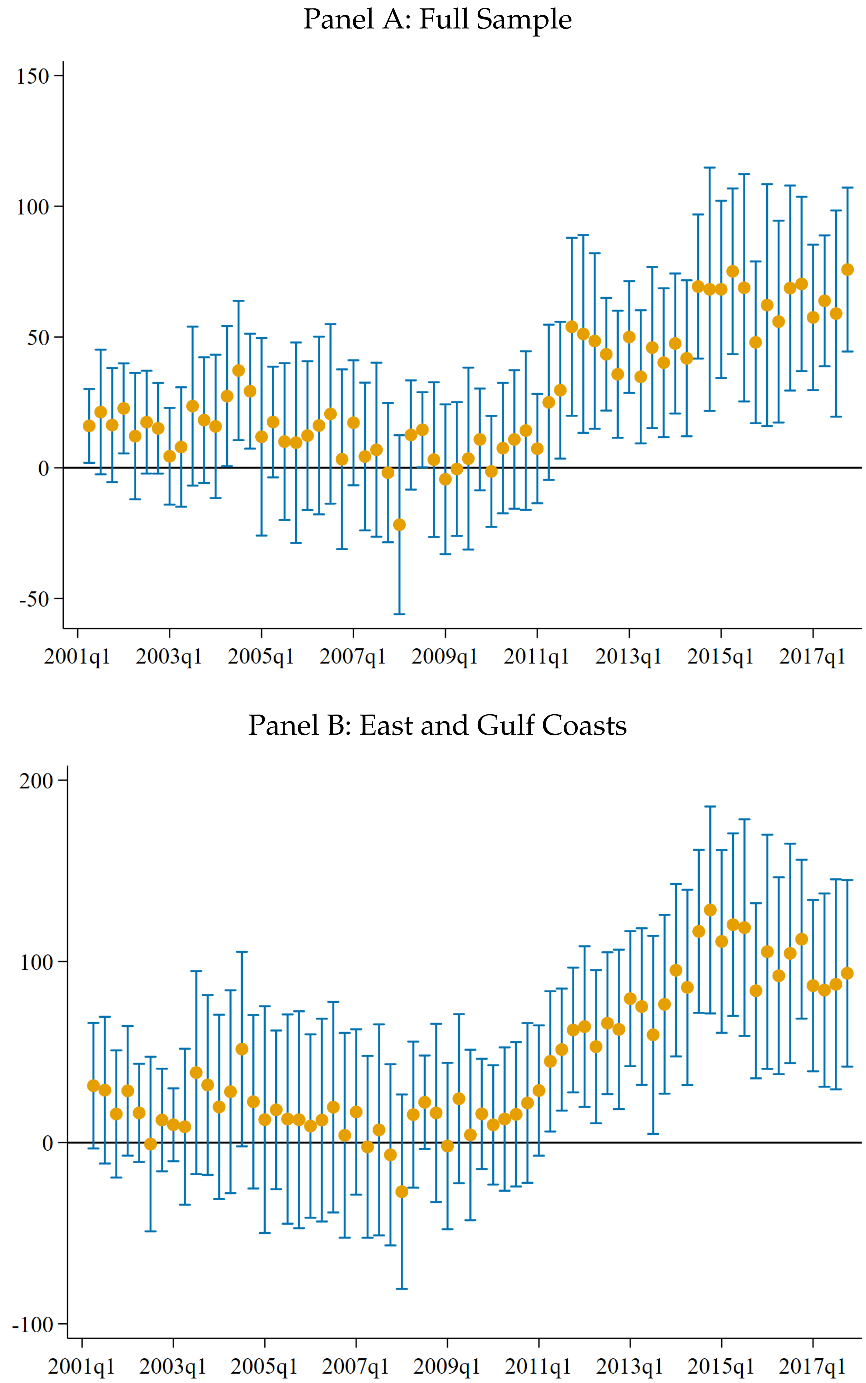


Panel C: West Coast



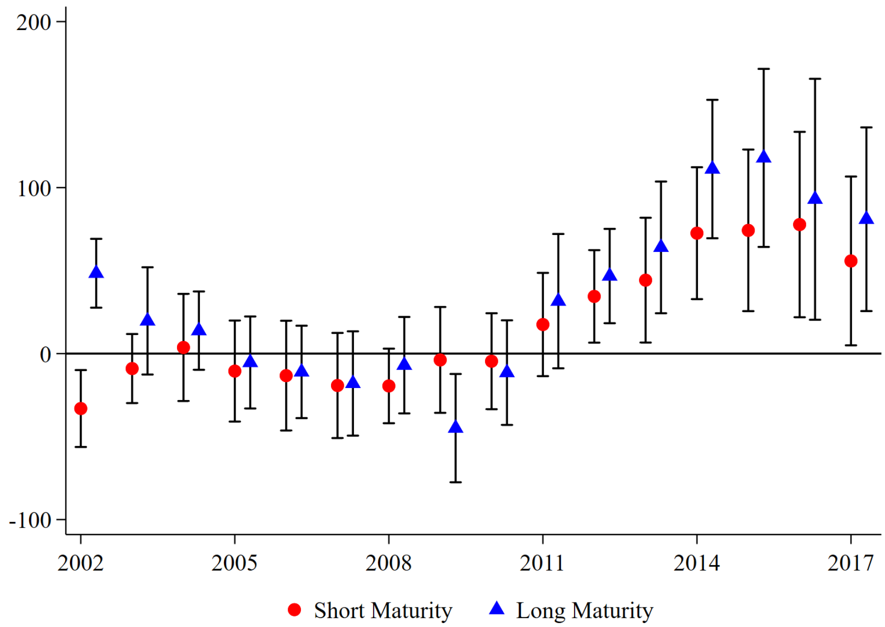
Note: This figure maps the fraction of properties in coastal school districts that is exposed to chronic tidal flooding after six feet of global average sea level rise. Gray areas represent districts that do not appear in the sample of municipal bonds described in Section 2. For ease of presentation, we break the states into three regions, with Panel A focusing on the Northeast, Panel B on the Southeast and Gulf Coast, and Panel C on the West Coast.

Figure 4: Effect of Sea Level Rise Exposure on Bond Credit Spreads



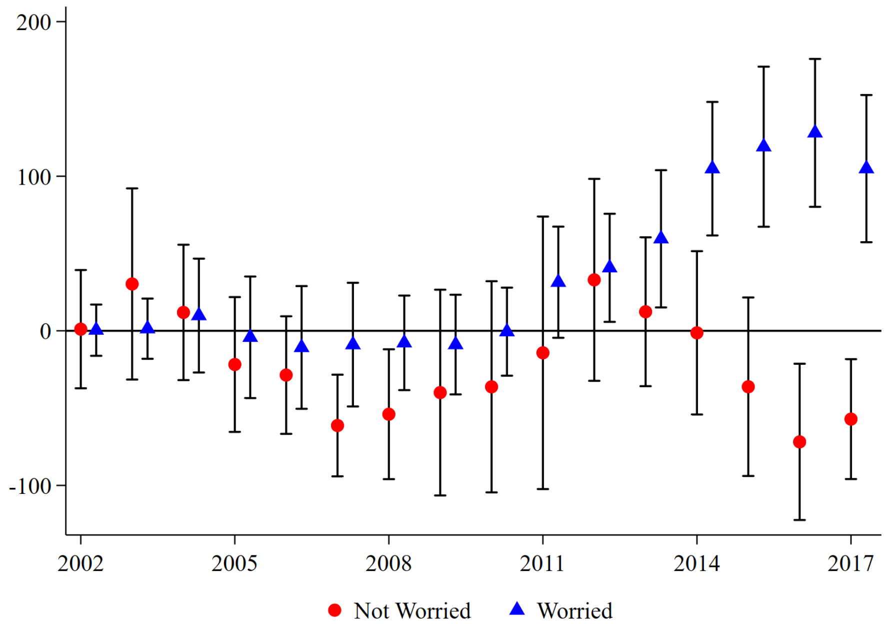
Note: This figure plots the quarterly effect of SLR exposure on municipal bond credit spreads. Spread is defined as the difference, in basis points, between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. The coefficients come from a regression with the same structure as equation (1), with quarterly instead of yearly interaction coefficients, including county-year-month and district fixed effects and controls for liquidity and the term structure of credit spreads. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. The vertical bars denote 95% confidence intervals based on standard errors are clustered by school district and month.

Figure 5: Heterogeneous Effects of SLR Exposure by Maturity



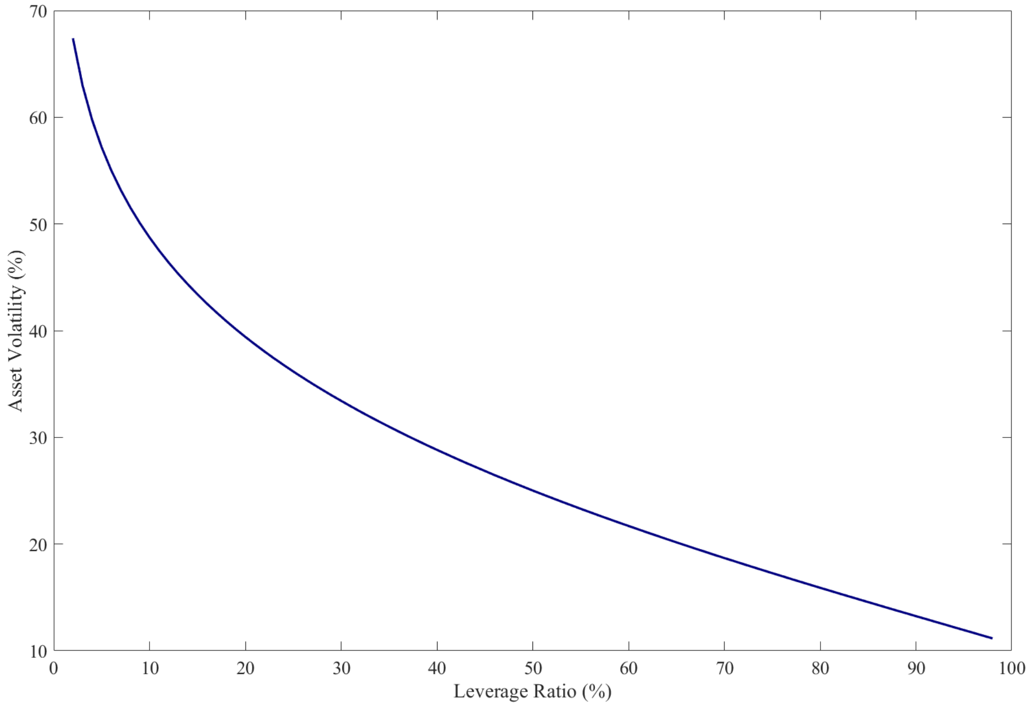
Note: This figure plots the yearly effect of SLR exposure on municipal bond credit spreads for bonds issued by school districts on the East and Gulf coasts. Spread is defined as the difference, in basis points, between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. The coefficients come from a similar regression to equation (1), with the Frac. Exposed $\times$ Year covariate interacted with an indicator for long-maturity bonds, including county-year-month fixed effects and controls for liquidity and the term structure of credit spreads. Long-maturity bonds are defined as having more than ten years remaining to maturity. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. The vertical bars denote 95% confidence intervals based on standard errors are clustered by school district and month.

Figure 6: Heterogeneous Effects of SLR Exposure by Local Beliefs



Note: This figure plots the yearly effect of SLR exposure on municipal bond credit spreads for bonds issued by school districts on the East and Gulf coasts. Spread is defined as the difference, in basis points, between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. The coefficients come from a similar regression to equation (1), with the Frac. Exposed $\times$ Year covariate interacted with an indicator for states with an above-median level of concern about climate risk, including county-year-month fixed effects and controls for liquidity and the term structure of credit spreads. Worried states include (in order of concern) New York, Massachusetts, New Jersey, Rhode Island, Connecticut, and Maine, while not worried states include Texas, South Carolina, Mississippi, and Louisiana. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. The vertical bars denote 95% confidence intervals based on standard errors are clustered by school district and month.

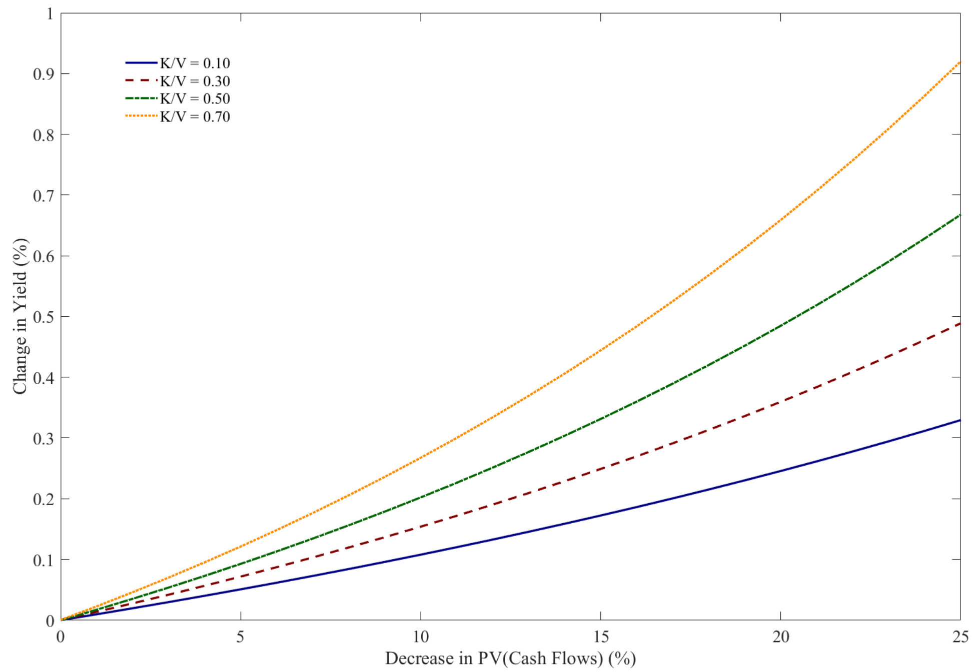
Figure 7: Model-Implied Asset Volatility as a Function of Leverage



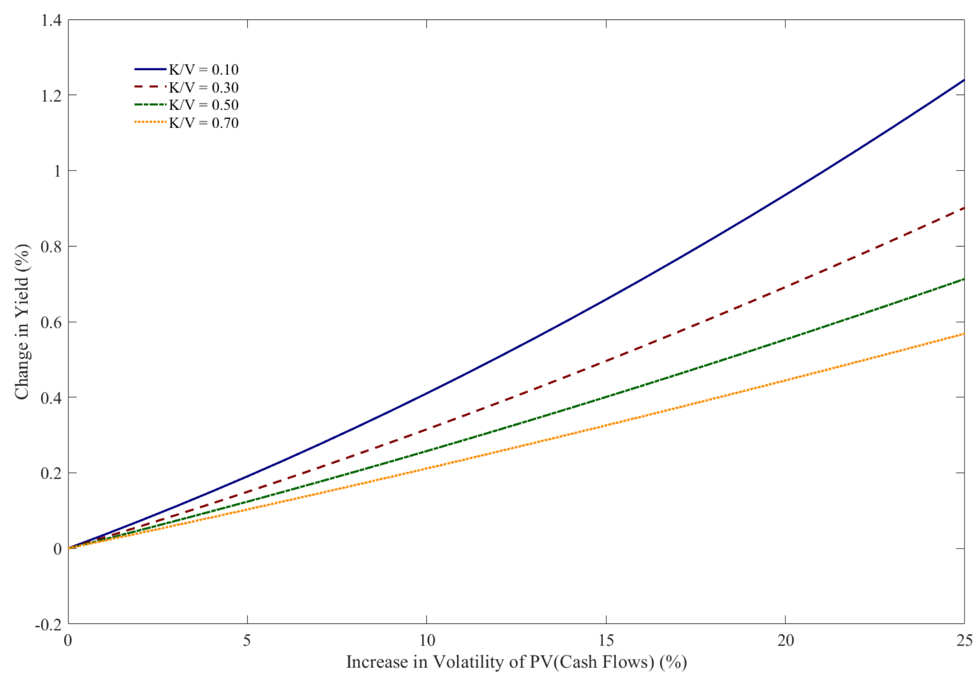
Note: This figure plots the model-implied volatility (σ) from equation (3) as a function of the leverage ratio (K/V). The other model parameters are: $y = 3.33\%$, $r = 2.70\%$, and $T = 7.5$.

Figure 8: Effects of Asset Value and Volatility Shocks on Municipal Bond Yields

Panel A: Decrease in Asset Value



Panel B: Increase in Asset Volatility



Note: This figure plots the change in yield associated with changes in the distribution of cash flows backing municipal bond repayment. Panel A considers reductions in the present value of cash flows, while Panel B considers proportional increases in the volatility of the underlying asset value. Each panel considers four parameter specifications based on leverage ratios (K/V) of 10%, 30%, 50%, and 70%, along with the associated model-implied volatilities from Figure 7. The other model parameters are: $y = 3.33\%$, $r = 2.70\%$, and $T = 7.5$.

Table 1: Summary Statistics

	Full Coastal Sample			*SLR Exposed Districts*		
	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.
Fraction of Properties Exposed (6 foot SLR)	0.03	0.08	306,033	0.06	0.12	140,984
Yield-to-Maturity (%)	3.33	1.25	306,033	3.29	1.23	140,984
MMA AAA-Rated Tax-Exempt Rate (%)	2.69	1.27	306,033	2.65	1.27	140,984
Spread over MMA Curve (bps)	63.13	58.31	306,033	62.89	57.73	140,984
Time to Maturity	9.94	6.20	306,033	9.70	6.00	140,984
Bond Age	4.03	2.75	306,033	3.98	2.68	140,984
Monthly Trading Volume ($000s)	621.9	3,920	306,033	789.9	5,185	140,984
Monthly S.D. of Price (per $100)	0.90	0.71	271,795	0.90	0.71	125,834

Note: This table reports the summary statistics for the main variables used in this paper. Observations are at the bond-year-month level. Sea Level Rise exposures are measured within school districts and represent the fraction of residential properties that would be inundated after a given level of global average sea level rise. SLR Exposed Districts are school districts with non-zero exposure to six feet of sea level rise.

Table 2: Effect of Sea Level Rise Exposure on Bond Spreads

Spread over MMA Curve (bps)	(1)	(2)	(3)	(4)	(5)	(6)
Frac. Exposed × 1(Year 2001)	−19.057∗∗	−18.408∗	−19.000∗∗	−7.777	−12.778∗∗	–
	(−2.08)	(−1.96)	(−2.06)	(−1.40)	(−1.99)	–
Frac. Exposed × 1(Year 2002)	−16.831∗∗	−23.231∗∗∗	−22.768∗∗∗	−10.711	−7.733	2.428
	(−2.33)	(−2.79)	(−2.66)	(−1.52)	(−0.94)	(0.74)
Frac. Exposed × 1(Year 2003)	−10.630∗	−18.131∗	−16.629∗	−11.447	−11.291	−0.286
	(−1.66)	(−1.84)	(−1.68)	(−1.34)	(−1.34)	(−0.05)
Frac. Exposed × 1(Year 2004)	−9.904	1.423	1.507	1.835	−1.200	13.534
	(−1.52)	(0.15)	(0.16)	(0.25)	(−0.17)	(1.61)
Frac. Exposed × 1(Year 2005)	−13.570∗∗	−4.323	−4.456	−5.865	−13.536	−2.073
	(−2.44)	(−0.39)	(−0.42)	(−0.72)	(−1.40)	(−0.20)
Frac. Exposed × 1(Year 2006)	−17.434∗∗∗	−1.352	−1.187	−2.016	−13.640	−1.319
	(−2.92)	(−0.11)	(−0.10)	(−0.20)	(−1.42)	(−0.11)
Frac. Exposed × 1(Year 2007)	−21.081∗∗∗	−12.468	−12.621∗	−10.700∗	−21.034∗∗∗	−7.105
	(−3.01)	(−1.65)	(−1.68)	(−1.68)	(−2.71)	(−0.63)
Frac. Exposed × 1(Year 2008)	−15.365∗	−22.141∗∗∗	−21.721∗∗∗	−17.212∗∗	−20.770∗∗	−12.030
	(−1.69)	(−3.17)	(−2.74)	(−2.19)	(−2.45)	(−1.32)
Frac. Exposed × 1(Year 2009)	−18.949	−31.222∗∗	−30.169∗∗	−25.742∗∗	−18.897∗∗	−12.071
	(−1.38)	(−2.30)	(−2.24)	(−2.29)	(−2.07)	(−1.10)
Frac. Exposed × 1(Year 2010)	−35.165∗∗	−24.884∗∗	−24.294∗∗	−19.629∗∗∗	−10.089	−6.275
	(−2.57)	(−2.11)	(−2.06)	(−2.66)	(−1.24)	(−0.58)
Frac. Exposed × 1(Year 2011)	−8.295	0.417	0.726	0.752	9.027	12.879
	(−0.63)	(0.03)	(0.06)	(0.06)	(0.63)	(0.80)
Frac. Exposed × 1(Year 2012)	−25.918∗	−0.947	0.991	1.127	31.391∗∗∗	31.454∗∗
	(−1.85)	(−0.09)	(0.08)	(0.11)	(2.66)	(2.45)
Frac. Exposed × 1(Year 2013)	−15.368	7.748	8.093	5.586	26.106∗∗	28.760∗∗
	(−1.28)	(1.08)	(1.03)	(0.70)	(2.18)	(2.22)
Frac. Exposed × 1(Year 2014)	−9.863	7.201	5.606	3.082	36.770∗∗	42.415∗∗
	(−0.56)	(0.64)	(0.49)	(0.26)	(2.14)	(2.45)
Frac. Exposed × 1(Year 2015)	−3.751	14.013	13.537	14.630	44.333∗∗	50.826∗∗
	(−0.11)	(0.72)	(0.70)	(0.86)	(2.26)	(2.56)
Frac. Exposed × 1(Year 2016)	−9.604	9.039	8.003	13.528	40.040∗∗	49.383∗∗
	(−0.24)	(0.34)	(0.30)	(0.58)	(1.97)	(2.26)
Frac. Exposed × 1(Year 2017)	−8.058	1.774	1.718	2.264	37.812∗∗∗	49.554∗∗∗
	(−0.35)	(0.12)	(0.11)	(0.17)	(2.69)	(3.04)
Controls	N	Y	Y	Y	Y	Y
Year-Month FE	N	N	Y	N	N	N
State-Year-Month FE	N	N	N	Y	N	N
County-Year-Month FE	N	N	N	N	Y	Y
District FE	N	N	N	N	N	Y
Observations	306,033	271,795	271,795	271,582	270,297	270,297

Note: This table reports estimates of equation (1) in the full sample of bonds issued by school districts in coastal states. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. Standard errors are clustered by school district and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table 3: Effect of Sea Level Rise Exposure and Bond Spreads by Regional Sample

Spread over MMA Curve (bps)	(1)	(2)	(3)	(4)
Frac. Exposed × 1(Year 2002)	−6.556	−3.659	8.083	10.310
	(−0.72)	(−0.44)	(1.52)	(1.51)
Frac. Exposed × 1(Year 2003)	1.862	4.899	−2.324	−4.242
	(0.27)	(0.74)	(−0.22)	(−0.30)
Frac. Exposed × 1(Year 2004)	10.543	8.349	18.059	13.365
	(0.75)	(0.68)	(1.52)	(0.97)
Frac. Exposed × 1(Year 2005)	−4.665	−5.000	15.920	−4.227
	(−0.33)	(−0.41)	(0.87)	(−0.24)
Frac. Exposed × 1(Year 2006)	−8.187	−7.531	53.839***	35.776*
	(−0.57)	(−0.61)	(3.07)	(1.85)
Frac. Exposed × 1(Year 2007)	−14.894	−12.772	31.227	10.299
	(−1.01)	(−0.96)	(1.57)	(0.51)
Frac. Exposed × 1(Year 2008)	−13.600	−9.342	12.299	10.648
	(−1.20)	(−0.91)	(0.57)	(0.44)
Frac. Exposed × 1(Year 2009)	−10.114	−9.323	−1.255	5.879
	(−0.76)	(−0.74)	(−0.04)	(0.20)
Frac. Exposed × 1(Year 2010)	−6.061	−6.468	23.005	32.923
	(−0.50)	(−0.58)	(0.69)	(0.89)
Frac. Exposed × 1(Year 2011)	23.605	21.952	7.232	21.664
	(1.40)	(1.39)	(0.12)	(0.32)
Frac. Exposed × 1(Year 2012)	39.436***	32.290**	34.955	51.888
	(2.80)	(2.35)	(0.59)	(0.74)
Frac. Exposed × 1(Year 2013)	52.599***	46.693***	−11.663	0.776
	(2.93)	(2.74)	(−0.50)	(0.04)
Frac. Exposed × 1(Year 2014)	84.252***	79.303***	−46.501*	−32.539
	(4.45)	(4.54)	(−1.71)	(−1.38)
Frac. Exposed × 1(Year 2015)	86.491***	86.610***	−24.541	−26.051
	(3.57)	(3.77)	(−1.17)	(−1.08)
Frac. Exposed × 1(Year 2016)	81.057***	83.013***	−0.011	−15.727
	(2.72)	(2.96)	(−0.00)	(−0.98)
Frac. Exposed × 1(Year 2017)	67.528***	74.271***	27.026**	3.082
	(2.74)	(3.25)	(2.19)	(0.31)
Sample	East & Gulf	East & Gulf	West	West
Exposure	Any	Non-Zero	Any	Non-Zero
Controls	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y
District FE	Y	Y	Y	Y
Observations	148,840	104,329	121,457	55,511

Note: This table reports estimates of equation (1) with the sample split into two regions. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond. East & Gulf includes Connecticut, Louisiana, Maine, Massachusetts, Mississippi, New Jersey, New York, Rhode Island, South Carolina, and Texas. West includes California. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. Standard errors are clustered by school district and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table 4: Effect of Sea Level Rise Exposure and Bond Spreads by Maturity

Spread over MMA Curve (bps)	(1)	(2)	(3)	(4)
Frac. Exposed $\times$ 1(Post)	62.792***	24.217***	58.674***	-
	(4.36)	(3.62)	(3.46)	-
Log(Maturity) $\times$ 1(Post)			33.756***	33.769***
			(12.17)	(9.52)
Frac. Exposed $\times$ Log(Maturity)			3.823	-1.443
			(0.44)	(-0.14)
Frac. Exposed $\times$ 1(Post) $\times$ Log(Maturity)			5.555	13.434**
			(0.99)	(2.38)
Sample	East & Gulf	East & Gulf	East & Gulf	East & Gulf
Maturity Range	$<$ 10 years	$\geq$ 10 years	All	All
Controls	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	N
District FE	Y	Y	Y	N
District-Year-Month FE	N	N	N	Y
Observations	84,686	62,141	148,840	140,515

Note: This table reports estimates of equation (1) in the East and Gulf coast sample, adding an interaction with the bond's remaining time to maturity in years. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Post is an indicator equal to one for observations occurring in the year 2012 or later. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. Standard errors are clustered by school district and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table 5: Effect of Sea Level Rise Exposure and Bond Spreads by Local Beliefs

Spread over MMA Curve (bps)	(1)	(2)	(3)
Frac. Exposed $\times$ 1(Post)	78.087***	10.169	77.133***
	(6.31)	(1.00)	(6.15)
Frac. Exposed $\times$ 1(Post) $\times$ State Worry			40.987***
			(3.69)
Sample	East & Gulf	East & Gulf	East & Gulf
Level of Concern	Worried	Not Worried	All
Controls	Y	Y	Y
County-Year-Month FE	Y	Y	Y
District FE	Y	Y	Y
Observations	69,270	79,570	148,840

Note: This table reports estimates of equation (1) in the East and Gulf coast sample, adding an interaction with state residents' level of concern about global warming. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average spread of a municipal bond. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Post is an indicator equal to one for observations occurring in the year 2012 or later. State Worry is a standardized measure of global warming concerns from the Yale Climate Opinions map. Worried states include (in order of concern) New York, Massachusetts, New Jersey, Rhode Island, Connecticut, and Maine, while not worried states include Texas, South Carolina, Mississippi, and Louisiana. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. Standard errors are clustered by school district and year-month.

Table 6: Model-Implied Changes in Credit Spreads due to Economic Shocks

T	7.5	7.5	7.5	22.5	22.5
y (%)	3.33	3.33	3.33	4.70	5.81
r (%)	2.70	2.70	2.70	4.00	4.00
α (%)	0	25	0	0	0
K_S/K (%)	0	0	50	0	0
K/V (%)	40	40	40	40	40
σ (%)	27.8	24.8	23.9	30.6	41.3
ΔV = -1%	0.015	0.018	0.019	0.007	0.012
ΔV = -5%	0.081	0.093	0.104	0.039	0.060
ΔV = -10%	0.174	0.203	0.230	0.083	0.125
ΔV = -20%	0.412	0.488	0.564	0.184	0.273
$\Delta\sigma$ = +1%	0.026	0.026	0.030	0.026	0.052
$\Delta\sigma$ = +5%	0.137	0.134	0.159	0.133	0.264
$\Delta\sigma$ = +10%	0.287	0.279	0.335	0.276	0.541
$\Delta\sigma$ = +20%	0.623	0.599	0.734	0.591	1.135

Note: This table reports estimates from alternative specifications of the structural model of credit risk described in Section 4.1. All specifications hold the leverage ratio (K/V) fixed at 40%, the average of the four ratios considered in Figure 8, and compute the implied asset volatility based on this and the other model parameters. The top panel of the table reports the parameters associated with the specification in each column, while the bottom panel reports the change in yield (in percentage terms) from proportional reductions in asset values and increases in volatility listed in the rows. The first three specifications are the baseline used in Figure 8, the baseline with a proportional bankruptcy cost of 25%, and the baseline with a debt structure of 50% senior loans and 50% junior bonds. The last two specifications are based on the mean and 90th percentile credit spreads, respectively, of new issue municipal bonds with 25 years or more to maturity.

Sea Level Rise Exposure and Municipal Bond Yields
Internet Appendix

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Michael Schwert§

May 8, 2020

This appendix provides supplementary analysis for "Sea Level Rise Exposure and Municipal Bond Yields." First, provide supplementary tables and figures to support the conclusions in the paper. Second, we replicate our findings on a less restricted sample of school district bonds. Third, we present estimates of the structural model of credit risk using tax-adjusted yields as in Schwert (2017). Finally, we replicate the results in Painter (2020) to shed light on differences in our findings.

Contents

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1 Supplementary Evidence on the Main Sample

Table A1: Sample Breakdown by Year

Year	(1)	(2)	(3)
2001	10,075	8,719	6,596
2002	12,664	10,997	7,995
2003	19,148	17,033	11,181
2004	23,335	21,092	13,373
2005	26,012	23,521	14,279
2006	30,131	27,282	16,795
2007	31,508	28,302	17,168
2008	33,530	30,023	18,365
2009	39,360	35,571	21,756
2010	43,493	39,294	23,904
2011	45,678	41,314	24,957
2012	40,789	37,000	22,513
2013	44,377	40,397	24,407
2014	38,461	35,131	20,923
2015	36,518	33,645	19,945
2016	36,871	34,228	19,881
2017	41,739	38,720	21,995

Note: This table reports the number of observations by year. Column (1) reports the bond-year-month observations after the sample selection described in the paper. Column (2) reports the number of observations from county-year-months with more than one school district with a traded bond. Column (3) reports the number of observations after applying the restriction in (2) and requiring that each district in the sample have at least one bond trade in each year from 2001 to 2017.

Table A2: Sample Breakdown by State

State	(1)	(2)	(3)
California	219,438	219,258	137,193
Connecticut	7,713	7,713	922
Florida	34,928	299	0
Georgia	1,353	43	0
Louisiana	2,978	1,241	1,173
Maine	1,675	1,601	273
Maryland	778	0	0
Massachusetts	15,416	15,415	2,457
Mississippi	875	739	650
New Jersey	83,181	83,181	37,940
New York	66,381	66,381	38,380
North Carolina	4,025	692	0
Oregon	1,173	0	0
Rhode Island	1,375	1,375	385
South Carolina	15,153	8,131	7,380
Texas	97,091	96,200	79,280
Virginia	134	0	0
Washington	22	0	0

Note: This table reports the number of observations by state. Column (1) reports the bond-year-month observations after the sample selection described in the paper. Column (2) reports the number of observations from county-year-months with more than one school district with a traded bond. Column (3) reports the number of observations after applying the restriction in (2) and requiring that each district in the sample have at least one bond trade in each year from 2001 to 2017.

Table A3: Effect of SLR Exposure on Bond Spreads – Alternative Exposure Levels

Spread over MMA Curve (bps)	(1)	(2)	(3)	(4)	(5)	(6)
Frac. Exposed × 1(Year 2002)	2.428	8.232	18.479	-4.929	-3.946	-24.198
	(0.74)	(1.06)	(0.57)	(-0.57)	(-0.33)	(-0.54)
Frac. Exposed × 1(Year 2003)	-0.286	-0.205	-40.439	1.424	1.623	-37.790
	(-0.05)	(-0.01)	(-0.90)	(0.19)	(0.13)	(-0.69)
Frac. Exposed × 1(Year 2004)	13.534	26.053	42.930	10.323	19.128	24.892
	(1.61)	(1.15)	(0.77)	(0.74)	(0.73)	(0.32)
Frac. Exposed × 1(Year 2005)	-2.073	-6.808	28.850	-6.579	-14.954	21.122
	(-0.20)	(-0.31)	(0.51)	(-0.46)	(-0.63)	(0.38)
Frac. Exposed × 1(Year 2006)	-1.319	-4.900	39.656	-9.731	-14.374	35.832
	(-0.11)	(-0.21)	(0.64)	(-0.67)	(-0.58)	(0.62)
Frac. Exposed × 1(Year 2007)	-7.105	-10.735	2.135	-15.958	-24.068	-20.770
	(-0.63)	(-0.47)	(0.03)	(-1.10)	(-1.02)	(-0.34)
Frac. Exposed × 1(Year 2008)	-12.030	-26.534	-36.551	-14.048	-22.676	-30.984
	(-1.32)	(-1.42)	(-0.62)	(-1.25)	(-1.19)	(-0.51)
Frac. Exposed × 1(Year 2009)	-12.071	-29.318	-75.565	-10.069	-12.199	-5.243
	(-1.10)	(-1.22)	(-1.04)	(-0.76)	(-0.51)	(-0.06)
Frac. Exposed × 1(Year 2010)	-6.275	-24.795	-92.423	-5.453	-9.507	-47.436
	(-0.58)	(-1.20)	(-1.36)	(-0.44)	(-0.50)	(-0.64)
Frac. Exposed × 1(Year 2011)	12.879	3.716	-132.000	24.553	39.449	-7.320
	(0.80)	(0.12)	(-1.59)	(1.43)	(1.41)	(-0.08)
Frac. Exposed × 1(Year 2012)	31.454**	32.208	-14.152	40.402***	67.012***	122.154
	(2.45)	(1.25)	(-0.17)	(2.90)	(2.68)	(1.11)
Frac. Exposed × 1(Year 2013)	28.760**	45.243	22.686	52.181***	87.696***	159.412*
	(2.22)	(1.53)	(0.33)	(2.96)	(2.86)	(1.77)
Frac. Exposed × 1(Year 2014)	42.415**	90.458**	95.482	84.577***	159.416***	444.083***
	(2.45)	(2.49)	(1.04)	(4.45)	(4.97)	(4.24)
Frac. Exposed × 1(Year 2015)	50.826**	101.312**	71.928	87.164***	163.231***	390.344**
	(2.56)	(2.32)	(0.65)	(3.60)	(3.69)	(2.46)
Frac. Exposed × 1(Year 2016)	49.383**	116.632**	75.776	81.690***	152.792***	224.898
	(2.26)	(2.49)	(0.80)	(2.78)	(2.91)	(1.58)
Frac. Exposed × 1(Year 2017)	49.554***	129.338***	185.393**	67.155***	132.421***	233.639
	(3.04)	(3.65)	(2.08)	(2.73)	(3.00)	(1.61)
Sample	Full	Full	Full	East & Gulf	East & Gulf	East & Gulf
SLR Exposure	6 feet	4 feet	2 feet	6 feet	4 feet	2 feet
Controls	Y	Y	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Frac. Exposed Mean	0.026	0.013	0.005	0.030	0.016	0.006
Frac. Exposed SD	0.084	0.041	0.015	0.094	0.051	0.015
Observations	270,297	270,297	270,297	148,840	148,840	148,840

Note: This table reports regression estimates for the full sample of bonds issued by school districts in coastal states. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. Frac. Exposed is defined as the fraction of residential properties that would be inundated by two, four, or six feet of sea level rise. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. The regression includes county-year-month and school district fixed effects, with the year 2001 as the omitted category. Standard errors are clustered by school district and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table A4: Effect of SLR Exposure on Bond Spreads – Additional Controls

	(1)	(2)
Frac. Exposed × 1(Year 2002)	-15.530	-1.512
	(-1.53)	(-0.23)
Frac. Exposed × 1(Year 2003)	-3.467	8.721
	(-0.51)	(0.97)
Frac. Exposed × 1(Year 2004)	2.900	13.655
	(0.24)	(0.84)
Frac. Exposed × 1(Year 2005)	-8.403	7.670
	(-0.71)	(0.46)
Frac. Exposed × 1(Year 2006)	-17.759	-2.589
	(-1.45)	(-0.15)
Frac. Exposed × 1(Year 2007)	-14.830	3.039
	(-1.18)	(0.18)
Frac. Exposed × 1(Year 2008)	-17.127*	2.141
	(-1.68)	(0.16)
Frac. Exposed × 1(Year 2009)	-19.931	3.991
	(-1.59)	(0.27)
Frac. Exposed × 1(Year 2010)	-16.200	6.817
	(-1.33)	(0.49)
Frac. Exposed × 1(Year 2011)	6.350	32.480**
	(0.38)	(2.09)
Frac. Exposed × 1(Year 2012)	18.272	45.761***
	(1.31)	(2.91)
Frac. Exposed × 1(Year 2013)	37.653**	57.471***
	(2.21)	(2.87)
Frac. Exposed × 1(Year 2014)	69.701***	97.426***
	(3.66)	(4.93)
Frac. Exposed × 1(Year 2015)	74.453***	109.023***
	(2.99)	(4.44)
Frac. Exposed × 1(Year 2016)	75.469**	112.778***
	(2.51)	(4.76)
Frac. Exposed × 1(Year 2017)	60.905**	100.307***
	(2.45)	(4.48)
Log(Median House Price)		-13.142**
		(-2.01)
Controls	Y	Y
Coastal Distance × Year Control	Y	N
District FE	Y	Y
County-Year-Month FE	Y	Y
Outcome Mean	60.824	61.592
Outcome SD	54.588	55.448
Observations	189,323	160,887

Note: This table reports regression estimates for the full sample of bonds issued by school districts in coastal states. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. Column (1) controls for distance to coast, which is constructed by measuring the distance from the centroid of the school district to the nearest coastal feature, interacted with the year. Column (2) includes the logarithm of the median house price at the district-year level using data from Zillow's ZTRAXX transaction database. Standard errors are clustered by school district and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table A5: Effect of SLR Exposure on Bond Spreads – Value-Weighted SLR Exposure

	(1)	(2)	(3)	(4)
Frac. Exposed VW × 1(Post)	40.297***	60.347***	78.148***	-
	(3.07)	(4.00)	(5.41)	-
Frac. Exposed VW × 1(Post) × State Worry			41.972***	
			(3.82)	
Frac. Exposed VW × 1(Post) × Log(Maturity)				32.102***
				(3.76)
Controls	Y	Y	Y	Y
Subsample	Full	East & Gulf	East & Gulf	East & Gulf
District FE	Y	Y	Y	N
County-Year-Month FE	Y	Y	Y	N
District-Year-Month FE	N	N	N	Y
Observations	320,716	190,399	190,399	181,711

Note: This table reports regression estimates for the full sample of bonds issued by school districts in coastal states. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. Frac. Exposed VW is defined as the fraction of residential property value that would be inundated by six feet of sea level rise. Post is an indicator equal to one for observations occurring in the year 2012 or later. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. The regression includes county-year-month and school district fixed effects. Standard errors are clustered by school district and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table A6: Effect of SLR Exposure on Bond Spreads – Equal-Weighted by State

	(1)	(2)	(3)	(4)
Frac. Exposed × 1(Post)	45.032***	50.898***	63.239***	-
	(3.04)	(3.18)	(3.71)	-
Frac. Exposed × 1(Post) × State Worry			31.012***	
			(2.81)	
Frac. Exposed × 1(Post) × Log(Maturity)				32.661***
				(2.64)
Controls	Y	Y	Y	Y
Subsample	Full	East & Gulf	East & Gulf	East & Gulf
District FE	Y	Y	Y	N
County-Year-Month FE	Y	Y	Y	N
District-Year-Month FE	N	N	N	Y
Observations	320,716	190,399	190,399	181,711

Note: This table reports regression estimates for the full sample of bonds issued by school districts in coastal states. The regression is estimated using weighted least squares with weights corresponding to the inverse of the number of observations in the state-year bucket, which amounts to equally weighting our bond-year-month observations at the state-year level. The dependent variable is the volume-weighted average credit spread of a municipal bond. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Post is an indicator equal to one for observations occurring in the year 2012 or later. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. The regression includes county-year-month and school district fixed effects. Standard errors are clustered by school district and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table A7: Effect of SLR Exposure on Bond Spreads – County-Level Analysis

	(1)	(2)	(3)	(4)
Frac. Exposed × 1(2002)	-2.180	0.913	-2.529	-2.832
	(-0.94)	(0.20)	(-0.57)	(-0.42)
Frac. Exposed × 1(2003)	-4.301	1.774	-6.550	-2.986
	(-0.75)	(0.21)	(-0.96)	(-0.28)
Frac. Exposed × 1(2004)	-12.743**	-13.987**	-17.546***	-22.177***
	(-2.10)	(-2.03)	(-2.81)	(-2.73)
Frac. Exposed × 1(2005)	-18.207***	-16.772**	-22.474***	-23.241**
	(-2.76)	(-2.05)	(-3.18)	(-2.34)
Frac. Exposed × 1(2006)	-14.123**	-14.086*	-18.193***	-20.945**
	(-2.18)	(-1.95)	(-2.64)	(-2.30)
Frac. Exposed × 1(2007)	-20.166**	-17.528**	-25.159***	-26.850***
	(-2.59)	(-2.16)	(-3.07)	(-2.84)
Frac. Exposed × 1(2008)	-25.147**	-24.024	-31.352**	-34.014*
	(-2.04)	(-1.36)	(-2.50)	(-1.79)
Frac. Exposed × 1(2009)	-41.500**	-47.670	-44.082**	-50.010
	(-2.07)	(-1.50)	(-2.11)	(-1.49)
Frac. Exposed × 1(2010)	-45.406***	-52.485*	-46.751***	-48.950*
	(-2.79)	(-1.95)	(-2.78)	(-1.76)
Frac. Exposed × 1(2011)	-59.242***	-61.028**	-56.904***	-53.494*
	(-3.28)	(-1.99)	(-3.05)	(-1.69)
Frac. Exposed × 1(2012)	-55.767***	-65.086**	-52.138***	-57.941**
	(-3.26)	(-2.43)	(-3.05)	(-2.12)
Frac. Exposed × 1(2013)	-42.549***	-52.413**	-38.196**	-45.291*
	(-2.68)	(-2.25)	(-2.43)	(-1.92)
Frac. Exposed × 1(2014)	-40.676**	-48.130**	-35.775**	-41.909**
	(-2.48)	(-2.43)	(-2.18)	(-2.08)
Frac. Exposed × 1(2015)	-39.882**	-37.064**	-35.135*	-33.234*
	(-2.04)	(-2.09)	(-1.69)	(-1.78)
Frac. Exposed × 1(2016)	-46.150**	-35.137**	-41.680*	-30.440*
	(-2.35)	(-1.99)	(-1.96)	(-1.66)
Frac. Exposed × 1(2017)	-53.325***	-43.314**	-53.682***	-45.889**
	(-2.95)	(-2.51)	(-2.69)	(-2.45)
Sample	All	All	East & Gulf	East & Gulf
Controls	Y	Y	Y	Y
Issuer FE	Y	Y	Y	Y
State-Year-Month FE	Y	N	Y	N
CBSA-Year-Month FE	N	Y	N	Y
Outcome Mean	70.520	71.136	66.887	67.658
Outcome SD	72.865	73.162	69.233	69.589
Observations	4,155,458	4,044,098	2,774,213	2,664,984

Note: This table reports estimates of equation (1) in the universe of municipal bonds issued from issuers in coastal counties. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. Standard errors are clustered by state. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table A8: List of Sea Level Rise Studies

Author	Type	Year	Mid Scenario			High Scenario			
			Scenario	Mean	S.D.	Scenario	Mean	S.D.	
Church et al., 2001	IPCC Assessment Report	2001	SRES B1	0.33	0.12	SRES A2	0.45	0.15	
Meehl et al., 2007	IPCC Assessment Report	2007	SRES B1	0.28	0.05	SRES A2	0.43	0.11	
R. Horton et al., 2008	Semi-empirical	2008	SRES B1	0.65	0.05	SRES A2	0.79	0.05	
Vermeer & Rahmstorf, 2009	Semi-empirical	2009	SRES B1	0.9	0.21	SRES A2	1.07	0.25	
Grinsted et al., 2010	Semi-empirical	2010	SRES B1	0.9	0.09	SRES A2	0.95	0.21	
Hunter, 2010	Semi-empirical	2010	SRES B1	0.34	0.08	SRES A2	0.46	0.12	
Jevrejeva et al., 2010	Semi-empirical	2010	SRES B1	0.85	0.13	SRES A2	0.9	0.31	
Jevrejeva et al., 2012	Semi-empirical	2012	RCP4.5	0.81	0.15	RCP8.5	1.23	0.21	
Parris et al., 2012	Literature Synthesis	2012	NOAA	0.45	0.13	NOAA	1.25	0.38	*
Rahmstorf et al., 2012	Semi-empirical	2012	RCP4.5	0.92	0.24	RCP8.5	1.29	0.38	
Church et al., 2013	IPCC Assessment Report	2013	RCP4.5	0.54	0.18	RCP8.5	0.82	0.27	**
Perrette et al., 2013	Semi-empirical	2013	RCP4.5	0.89	0.22	RCP8.5	1.15	0.33	**
Jevrejeva et al., 2014	Probabilistic	2014	RCP4.5	0.55	0.08	RCP8.5	1.15	0.33	**
Kopp et al., 2014	Probabilistic	2014	RCP4.5	0.65	0.15	RCP8.5	0.87	0.18	**
Grinsted et al., 2015	Probabilistic	2015	RCP4.5	0.56	0.09	RCP8.5	1.14	0.35	**
Jevrejeva et al., 2016	Probabilistic	2016	RCP4.5	0.55	0.08	RCP8.5	1.16	0.32	**
Kopp et al., 2016	Semi-empirical	2016	RCP4.5	0.59	0.13	RCP8.5	0.92	0.2	**
Bakker et al., 2017	Probabilistic	2017	RCP4.5	0.76	0.11	RCP8.5	2	0.19	
Kopp et al., 2017	Probabilistic	2017	RCP4.5	1.04	0.28	RCP8.5	1.68	0.38	**
Le Bars et al., 2017	Probabilistic	2017	RCP4.5	1.04	0.28	RCP8.5	1.84	0.32	**
Nauels, Rogelj, et al., 2017	Probabilistic	2017	RCP4.5	0.64	0.31	RCP8.5	0.94	0.34	**
Wong et al., 2017	Probabilistic	2017	RCP4.5	0.93	0.19	RCP8.5	1.58	0.25	**

* NOAA report, distribution assumed across scenarios.
** Asymmetric distribution around mean

Note: This table reports a list of studies considered in creating the time-varying expectations of SLR risk described in Section 2.1 of the paper. Studies themselves report portions of the distribution (most commonly 5th and 95th percentile) or direct distributional information. In order to aggregate across studies, we assume normality to calculate the mean and standard deviation (in meters of SLR) from the distributional information supplied by each study. In some cases the distributions are right-skewed, so our assumption of normality induces a downward bias in our estimate of right-tail events. For a comprehensive overview of sea level rise research, see Garner et al. (2018)

2 Replication of Findings without Sample Restrictions

In this section, we replicate our main findings using a less restricted sample of school district bonds. This sample relaxes the "balanced panel" restriction used to ensure uniformity in our main sample. Specifically, the unrestricted sample drops the requirements that each county have more than one district and that each district have at least one secondary market bond price observation per year. Tables A1 and A2 in this Internet Appendix show the effects of these restrictions on our sample.

Table A9: Summary Statistics

	Full Coastal Sample			***SLR Exposed Districts***		
	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.
Fraction of Properties Exposed (6 foot SLR)	0.04	0.10	553,689	0.08	0.13	254,226
Yield-to-Maturity (%)	3.33	1.23	553,689	3.31	1.22	254,226
MMA AAA-Rated Tax-Exempt Rate (%)	2.68	1.26	553,689	2.66	1.25	254,226
Spread over MMA Curve (bps)	64.12	57.64	553,689	64.32	57.05	254,226
Time to Maturity	10.01	6.27	553,689	9.79	6.11	254,226
Bond Age	3.95	2.70	553,689	3.97	2.68	254,226
Monthly Trading Volume ($000s)	519.3	3,151	553,689	631.3	4,099	254,226
Monthly S.D. of Price	0.91	0.71	490,035	0.92	0.71	226,089

Note: This table reports the summary statistics for the main variables used in this paper. Observations are at the bond-year-month level. Sea Level Rise exposures are measured within school districts and represent the fraction of residential properties that would be inundated after a given level of global average sea level rise. SLR Exposed Districts are school districts with non-zero exposure to six feet of sea level rise.

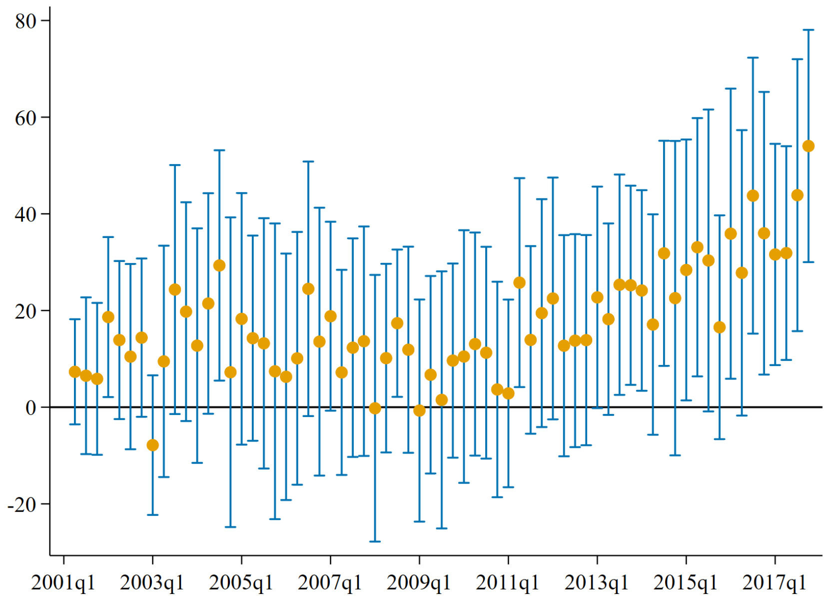
Table A10: Effect of Sea Level Rise Exposure on Bond Spreads

Spread over MMA Curve (bps)	(1)	(2)	(3)	(4)	(5)	(6)
Frac. Exposed × 1(Year 2001)	-12.925	-12.925	-13.406	-11.477*	-5.800	-
	(-1.47)	(-1.47)	(-1.55)	(-1.65)	(-1.12)	-
Frac. Exposed × 1(Year 2002)	13.004	13.004	13.403	10.031	-2.409	8.948*
	(0.96)	(0.96)	(0.99)	(1.05)	(-0.39)	(1.89)
Frac. Exposed × 1(Year 2003)	-0.788	-0.788	-1.296	-3.962	-1.638	6.841
	(-0.10)	(-0.10)	(-0.16)	(-0.50)	(-0.22)	(0.79)
Frac. Exposed × 1(Year 2004)	-1.897	-1.897	-2.153	-2.863	2.710	12.415
	(-0.20)	(-0.20)	(-0.23)	(-0.37)	(0.41)	(1.26)
Frac. Exposed × 1(Year 2005)	4.432	4.432	4.548	0.562	-2.409	8.045
	(0.47)	(0.47)	(0.49)	(0.07)	(-0.33)	(0.80)
Frac. Exposed × 1(Year 2006)	9.320	9.320	9.502	1.970	-0.233	8.275
	(0.91)	(0.91)	(0.94)	(0.25)	(-0.03)	(0.76)
Frac. Exposed × 1(Year 2007)	6.173	6.173	5.960	-4.920	-2.888	7.773
	(0.65)	(0.65)	(0.62)	(-0.89)	(-0.47)	(0.85)
Frac. Exposed × 1(Year 2008)	12.898	12.898	14.079	-9.423*	-5.194	4.716
	(0.80)	(0.80)	(0.87)	(-1.72)	(-0.77)	(0.55)
Frac. Exposed × 1(Year 2009)	7.442	7.442	8.189	-17.100**	-11.754*	-0.788
	(0.28)	(0.28)	(0.31)	(-2.37)	(-1.70)	(-0.09)
Frac. Exposed × 1(Year 2010)	11.288	11.288	11.506	-6.342	-5.639	4.651
	(0.49)	(0.49)	(0.50)	(-0.98)	(-0.84)	(0.51)
Frac. Exposed × 1(Year 2011)	16.514	16.514	16.429	-2.156	-0.289	9.800
	(0.79)	(0.79)	(0.79)	(-0.28)	(-0.04)	(1.02)
Frac. Exposed × 1(Year 2012)	2.973	2.973	5.467	-8.558	1.718	10.950
	(0.17)	(0.17)	(0.31)	(-1.18)	(0.21)	(1.16)
Frac. Exposed × 1(Year 2013)	8.811	8.811	6.759	-2.097	9.272	17.756*
	(0.92)	(0.92)	(0.69)	(-0.34)	(1.20)	(1.91)
Frac. Exposed × 1(Year 2014)	7.627	7.627	6.995	-1.653	8.161	19.028*
	(0.71)	(0.71)	(0.64)	(-0.19)	(0.77)	(1.68)
Frac. Exposed × 1(Year 2015)	10.717	10.717	9.929	2.937	12.058	22.143*
	(0.84)	(0.84)	(0.78)	(0.26)	(1.06)	(1.74)
Frac. Exposed × 1(Year 2016)	11.871	11.871	11.678	7.532	19.398	30.069**
	(0.87)	(0.87)	(0.85)	(0.55)	(1.56)	(2.14)
Frac. Exposed × 1(Year 2017)	13.334	13.334	13.684	4.349	20.584**	34.536***
	(1.60)	(1.60)	(1.64)	(0.61)	(2.35)	(3.24)
Controls	N	Y	Y	Y	Y	Y
Year-Month FE	N	N	Y	N	N	N
District FE	N	N	N	N	N	Y
State-Year-Month FE	N	N	N	Y	N	N
County-Year-Month FE	N	N	N	N	Y	Y
Observations	490,035	490,035	490,035	489,862	485,612	485,587

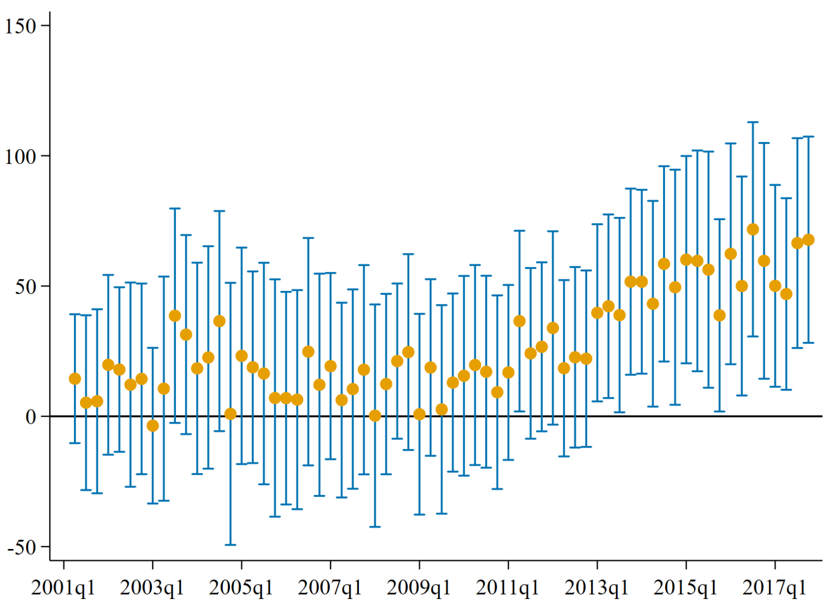
Note: This table reports estimates of equation (1) from the paper in the full sample of bonds issued by school districts in coastal states. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. Standard errors are clustered by school district and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Figure A1: Effect of Sea Level Rise Exposure on Bond Credit Spreads

Panel A: Full Sample



Panel B: East Coast Sample



Note: This figure plots the quarterly effect of SLR exposure on municipal bond credit spreads. Spread is defined as the difference, in basis points, between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. The coefficients come from a regression with the same structure as equation (1) from the paper, with quarterly instead of yearly interaction coefficients, including county-year-month and district fixed effects and controls for liquidity and the term structure of credit spreads. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. The vertical bars denote 95% confidence intervals based on standard errors are clustered by school district and month.

Table A11: Effect of Sea Level Rise Exposure and Bond Spreads by Regional Sample

Spread over MMA Curve (bps)	(1)	(2)	(3)	(4)
Frac. Exposed × 1(Year 2002)	8.269	8.500	1.873	5.841*
	(1.04)	(1.18)	(0.70)	(1.68)
Frac. Exposed × 1(Year 2003)	12.178	11.577	-8.199	-10.088
	(1.06)	(1.09)	(-0.91)	(-1.03)
Frac. Exposed × 1(Year 2004)	11.458	10.093	5.324	-1.554
	(0.82)	(0.78)	(0.44)	(-0.12)
Frac. Exposed × 1(Year 2005)	8.744	8.071	5.712	-9.913
	(0.68)	(0.68)	(0.43)	(-0.86)
Frac. Exposed × 1(Year 2006)	5.554	4.410	26.572	15.262
	(0.41)	(0.36)	(1.63)	(0.86)
Frac. Exposed × 1(Year 2007)	6.701	6.617	16.779	8.211
	(0.58)	(0.62)	(1.10)	(0.49)
Frac. Exposed × 1(Year 2008)	6.825	8.859	3.371	-5.696
	(0.63)	(0.88)	(0.19)	(-0.31)
Frac. Exposed × 1(Year 2009)	0.680	0.056	-5.300	-4.488
	(0.06)	(0.01)	(-0.26)	(-0.22)
Frac. Exposed × 1(Year 2010)	7.730	6.739	0.263	-0.478
	(0.70)	(0.63)	(0.01)	(-0.02)
Frac. Exposed × 1(Year 2011)	17.690*	16.922*	-7.407	-4.313
	(1.82)	(1.81)	(-0.19)	(-0.09)
Frac. Exposed × 1(Year 2012)	16.793*	12.558	3.964	20.070
	(1.68)	(1.29)	(0.10)	(0.41)
Frac. Exposed × 1(Year 2013)	36.119***	32.830***	-29.991	-20.256
	(3.28)	(3.14)	(-1.26)	(-0.86)
Frac. Exposed × 1(Year 2014)	43.279***	40.715***	-51.029**	-43.054*
	(3.36)	(3.28)	(-2.20)	(-1.90)
Frac. Exposed × 1(Year 2015)	45.559***	44.591***	-42.801**	-45.425**
	(3.00)	(3.02)	(-2.42)	(-2.05)
Frac. Exposed × 1(Year 2016)	51.883***	52.029***	-20.143	-36.091*
	(3.03)	(3.15)	(-1.16)	(-1.98)
Frac. Exposed × 1(Year 2017)	49.646***	51.591***	6.216	-4.610
	(3.57)	(3.86)	(0.47)	(-0.37)
Sample	East & Gulf	East & Gulf	West	West
Exposure	Any	Non-Zero	Any	Non-Zero
Controls	Y	Y	Y	Y
District FE	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y
Observations	290,815	236,147	194,772	77,264

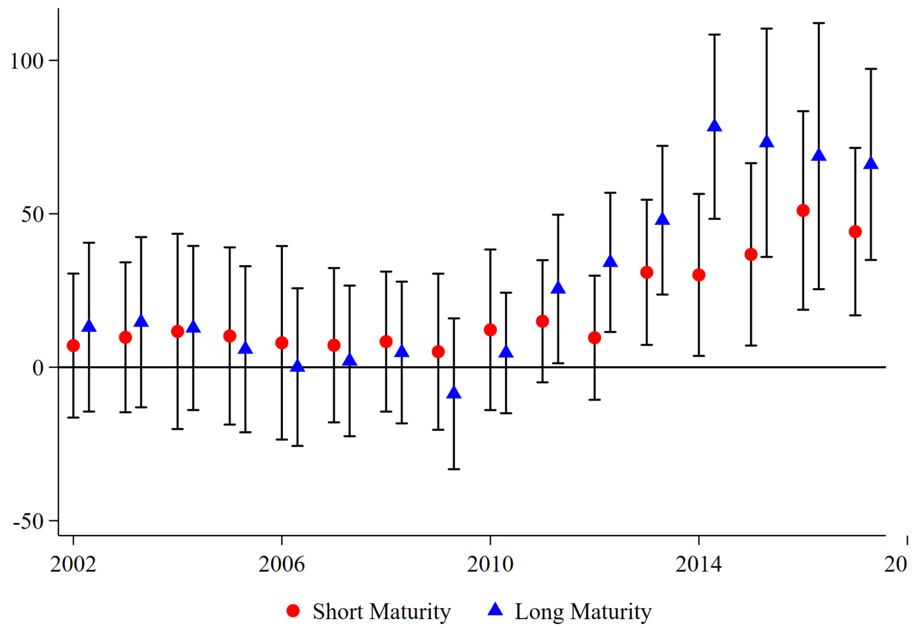
Note: This table reports estimates of equation (1) from the paper with the sample split into two regions. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond. East & Gulf includes Connecticut, Florida, Georgia, Louisiana, Maryland, Maine, Massachusetts, Mississippi, New Jersey, New York, North Carolina, Rhode Island, South Carolina, Texas, and Virginia. West includes California, Oregon, and Washington. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. Standard errors are clustered by school district and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table A12: Effect of Sea Level Rise Exposure and Bond Spreads by Maturity

Spread over MMA Curve (bps)	(1)	(2)	(3)	(4)
Frac. Exposed × 1(Post)	26.636***	9.664	-2.604	-
	(2.65)	(1.43)	(-0.12)	-
Log(Maturity) × 1(Post)			29.914***	31.539***
			(12.74)	(10.98)
Frac. Exposed × Log(Maturity)			-1.770	-5.411
			(-0.33)	(-0.98)
Frac. Exposed × Log(Maturity) × 1(Post)			18.164*	26.756**
			(1.77)	(2.52)
Sample	East & Gulf	East & Gulf	East & Gulf	East & Gulf
Maturity Range	$<$ 10 years	$\geq$ 10 years	All	All
Controls	Y	Y	Y	Y
District FE	Y	Y	Y	N
County-Year-Month FE	Y	Y	Y	N
District-Year-Month FE	N	N	N	Y
Observations	164,214	121,699	290,815	261,689

Note: This table reports estimates of equation (1) from the paper in the East and Gulf coast sample, adding an interaction with the bond's remaining time to maturity in years. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Post is an indicator equal to one for observations occurring in the year 2012 or later. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. Standard errors are clustered by school district and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Figure A2: Heterogeneous Effects of SLR Exposure by Maturity



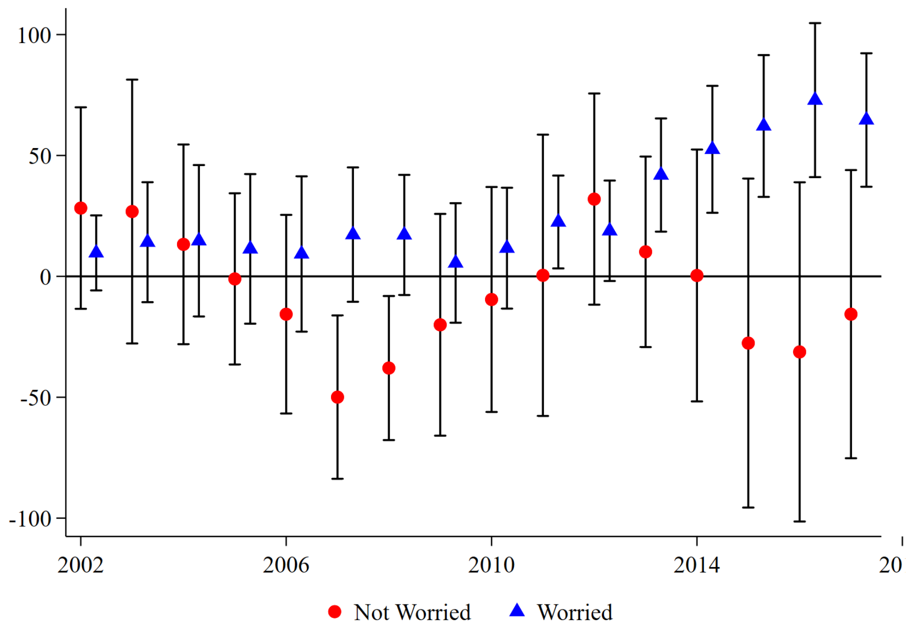
Note: This figure plots the yearly effect of SLR exposure on municipal bond credit spreads for bonds issued by school districts on the East and Gulf coasts. Spread is defined as the difference, in basis points, between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. The coefficients come from a similar regression to equation (1) from the paper, with the Frac. Exposed $\times$ Year covariate interacted with an indicator for long-maturity bonds, including county-year-month fixed effects and controls for liquidity and the term structure of credit spreads. Long maturity bonds are defined as having more than 10 years remaining to maturity. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. The vertical bars denote 95% confidence intervals based on standard errors are clustered by school district and month.

Table A13: Effect of Sea Level Rise Exposure and Bond Spreads by Local Beliefs

Spread over MMA Curve (bps)	(1)	(2)	(3)
Frac. Exposed × 1(Post)	34.412***	10.086	31.162***
	(3.17)	(0.65)	(2.86)
Frac. Exposed × 1(Post) × State Worry			17.149
			(1.63)
Sample	East & Gulf	East & Gulf	East & Gulf
Level of Concern	Worried	Not Worried	All
Controls	Y	Y	Y
District FE	Y	Y	Y
County-Year-Month FE	Y	Y	Y
Observations	152,487	138,328	290,815

Note: This table reports estimates of equation (1) from the paper in the East and Gulf coast sample, adding an interaction with state residents' level of concern about global warming. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average spread of a municipal bond. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. Post is an indicator equal to one for observations occurring in the year 2012 or later. State Worry is a standardized measure of global warming concerns from the Yale Climate Opinions map. Worried states include (in order of concern) New York, Massachusetts, New Jersey, Rhode Island, Connecticut, Maine, and Maryland, while not worried states include Texas, Florida, North Carolina, Virginia, South Carolina, Georgia, Mississippi, and Louisiana. Controls include the logarithm of the bond's time to maturity interacted with the year, and controls for liquidity including the coupon rate, years since issuance, log trading volume, and standard deviation of transaction prices. Standard errors are clustered by school district and year-month.

Figure A3: Heterogeneous Effects of SLR Exposure by Local Beliefs



Note: This figure plots the yearly effect of SLR exposure on municipal bond credit spreads for bonds issued by school districts on the East and Gulf coasts. Spread is defined as the difference, in basis points, between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. The coefficients come from a similar regression to equation (1) from the paper, with the Frac. Exposed × Year covariate interacted with an indicator for states with an above-median level of concern about climate risk, including county-year-month fixed effects and controls for liquidity and the term structure of credit spreads. Worried states include (in order of concern) New York, Massachusetts, New Jersey, Rhode Island, Connecticut, and Maine, while not worried states include Texas, South Carolina, Mississippi, and Louisiana. Frac. Exposed is defined as the fraction of residential properties that would be inundated by six feet of sea level rise. The vertical bars denote 95% confidence intervals based on standard errors are clustered by school district and month.

3 Structural Model with Tax-Adjusted Yields

The structural model of credit risk in the paper, based on Merton (1974), is usually applied to taxable corporate bond yields. In the paper, our calculation of the model parameters uses tax-exempt municipal bond yields and the Municipal Market Advisors AAA-rated tax-exempt curve as the risk-free benchmark. Under that approach, the parameters implied by municipal bond spreads account for the tax exemption's effect on the pricing of credit risk.

This section considers an alternative approach under which the model parameters are calibrated to tax-adjusted credit spreads as in Schwert (2017), using the LIBOR interest rate swap curve as the risk-free benchmark. Specifically, we take the yield of the typical tax-exempt municipal bond in our sample and adjust it upwards to its taxable-equivalent yield for the model calibration. Then we take the counterfactual yields from the model and adjust them back downwards by the same tax adjustment factor to obtain changes in tax-exempt yields implied by the model.

Under the assumption that the marginal tax rate impounded in tax-exempt bond yields is the top statutory income tax rate in each state, the tax adjustment factor is

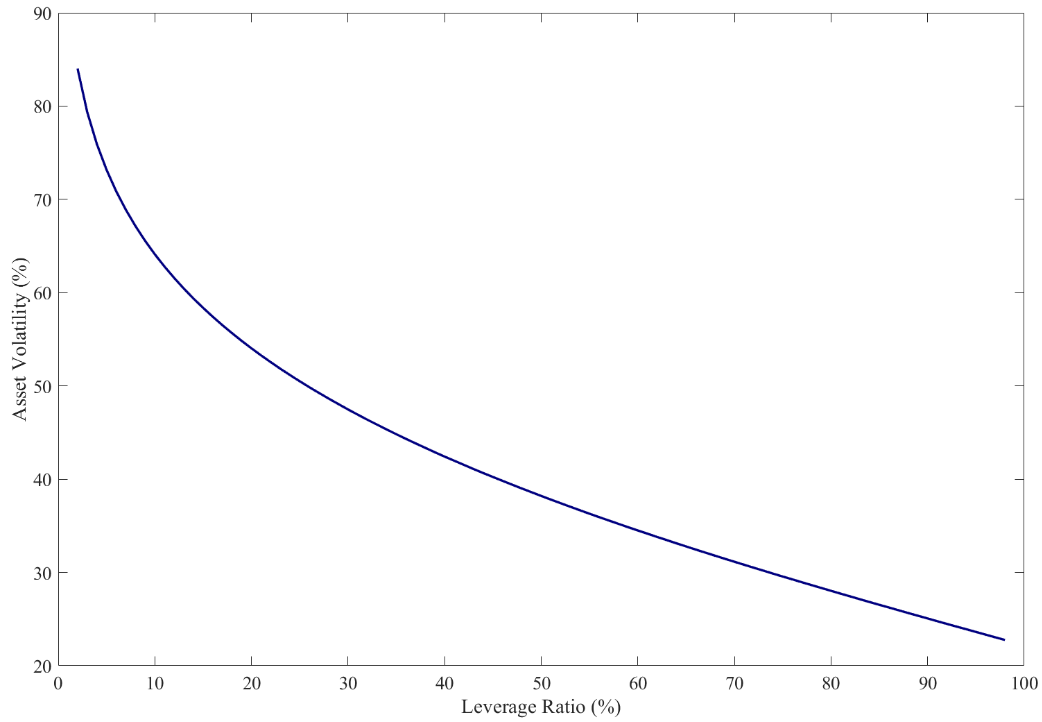
$$(1 - \tau_{s,t}) = (1 - \tau_t^{fed})(1 - \tau_{s,t}^{state}), \tag{1}$$

where τ_t^{fed} is the top federal income tax rate and $\tau_{s,t}^{state}$ is the top income tax rate in state s in year t. This formula accounts for the fact that state income tax payments are deductible from an individual's taxable income for federal taxes. Applying this tax adjustment factor and subtracting out the risk-free rate, the tax-adjusted spread on a tax-exempt municipal bond is

$$y_{i,t}^{TA} - r_t = \frac{y_{i,t}}{1 - \tau_{s,t}} - r_t. \tag{2}$$

For simplicity, we use the top federal tax rate of 35% that prevailed for most of our sample period and the average top state tax rate of 5%.

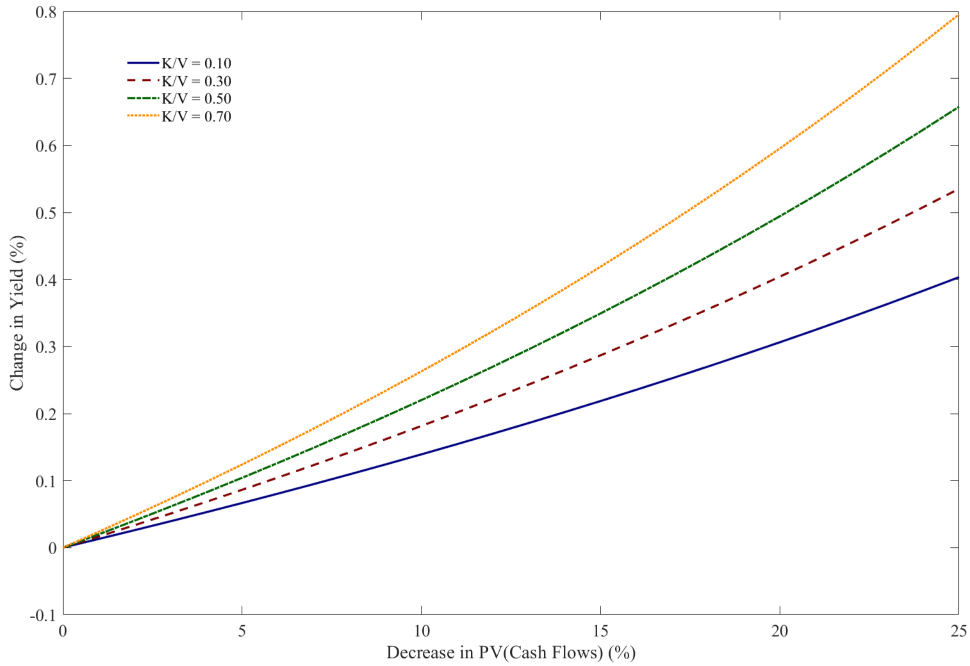
Figure A4: Model-Implied Asset Volatility as a Function of Leverage



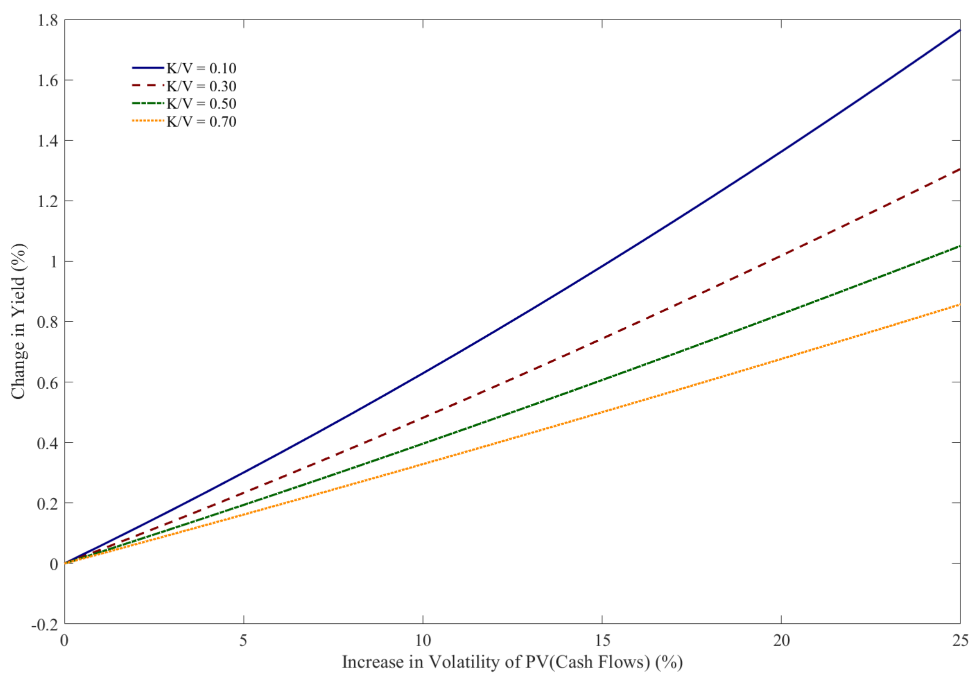
Note: This figure plots the model-implied volatility (σ) from equation (3) as a function of the leverage ratio (K/V). The model parameters are: $y^{TA} = 5.39\%$ $r = 3.10\%$, and $T = 7.5$.

Figure A5: Effects of Asset Value and Volatility Shocks on Municipal Bond Yields

Panel A: Decrease in Asset Value



Panel B: Increase in Asset Volatility



Note: This figure plots the change in yield associated with changes in the distribution of cash flows backing municipal bond repayment. Panel A considers reductions in the present value of cash flows, while Panel B considers proportional increases in the volatility of the underlying asset value. Each panel considers four parameter specifications based on leverage ratios (K/V) of 10%, 30%, 50%, and 70%, along with the associated model-implied volatilities from Figure A4. The other model parameters are: $y^{TA} = 5.39\%$ $r = 3.10\%$, and $T = 7.5$.

Table A14: Model-Implied Changes in Credit Spreads due to Economic Shocks

T	7.5	7.5	7.5	22.5	22.5
y (%)	3.33	3.33	3.33	4.70	5.81
y^{TA} (%)	5.39	5.39	5.39	7.61	9.41
r (%)	3.10	3.10	3.10	4.00	4.00
α (%)	0	25	0	0	0
K_S/K (%)	0	0	50	0	0
K/V (%)	40	40	40	40	40
σ (%)	41.9	38.1	34.9	53.9	64.2
ΔV = -1%	0.018	0.020	0.024	0.009	0.010
ΔV = -5%	0.094	0.106	0.127	0.047	0.052
ΔV = -10%	0.198	0.223	0.270	0.097	0.108
ΔV = -20%	0.444	0.501	0.617	0.209	0.230
$\Delta\sigma$ = +1%	0.042	0.040	0.045	0.054	0.075
$\Delta\sigma$ = +5%	0.214	0.201	0.231	0.275	0.380
$\Delta\sigma$ = +10%	0.440	0.411	0.472	0.562	0.776
$\Delta\sigma$ = +20%	0.923	0.854	0.981	1.169	1.614

Note: This table reports estimates from alternative specifications of the structural model of credit risk with tax-adjusted yields. All specifications hold the leverage ratio (K/V) fixed at 40%, the average of the four ratios considered in Figure A5, and compute the implied asset volatility based on this and the other model parameters. The top panel of the table reports the parameters associated with the specification in each column, while the bottom panel reports the change in yield (in percentage terms) from proportional reductions in asset values and increases in volatility listed in the rows. The first three specifications are the baseline used in Figure A5, the baseline with a proportional bankruptcy cost of 25%, and the baseline with a debt structure of 50% senior loans and 50% junior bonds. The last two specifications are based on the mean and 90th percentile credit spreads, respectively, of new issue municipal bonds with 25 years or more to maturity.

4 Replication of Painter (2020)

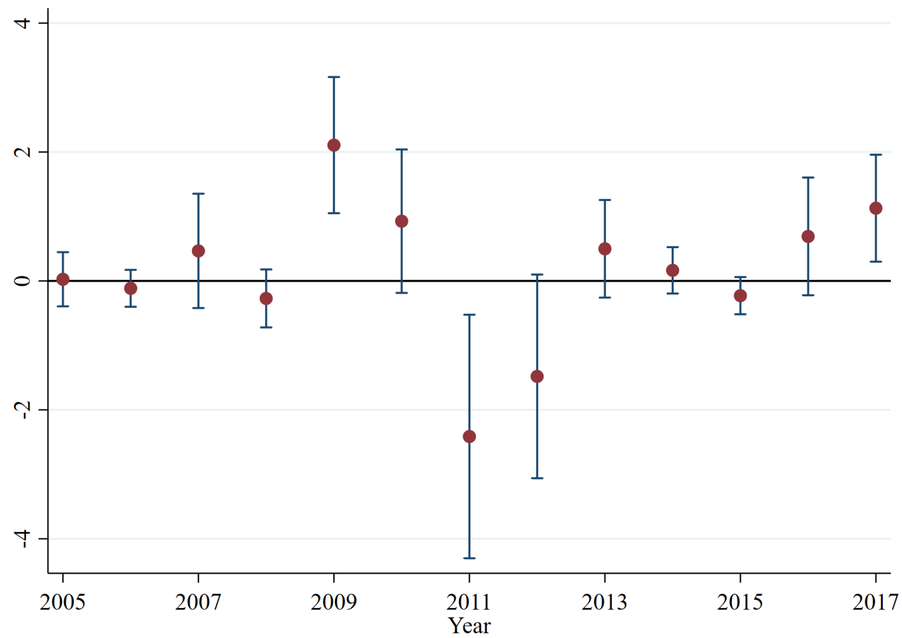
Painter (2020) finds that exposure to climate risk is associated with higher offering yields and gross spreads in the primary market for municipal bonds. His measure of climate risk exposure is based on Hallegatte et al. (2013), who estimate the expected annual loss from 40 cm (about 1.33 feet) of sea level rise as a percentage of GDP for a sample of coastal cities. He finds that a 1% increase in climate risk (i.e., loss of annual GDP) is associated with an increase in annualized issuance costs of 23.4 bps and an increase in offering yields of 16.1 bps. The effects are concentrated in long-maturity bond issues, with a maximum bond maturity of over 25 years, consistent with the idea that sea level rise will have larger effects in the future than in the near-term.

We replicate the analysis in Painter (2020) to understand the seemingly large effect of climate risk on bond yields and assess whether omitted factors contribute to the estimates. Marcus Painter generously provided the data from his paper to facilitate our replication. We estimate the regression from Table 3 of Painter (2020), using annualized issuance costs and the level of climate risk from Hallegatte et al. (2013) and interacting the climate risk coefficient with dummies for each calendar year, as in the regression setup from our paper. We find similar results if we use offering yield as the dependent variable or the logarithm of climate risk as the independent variable.

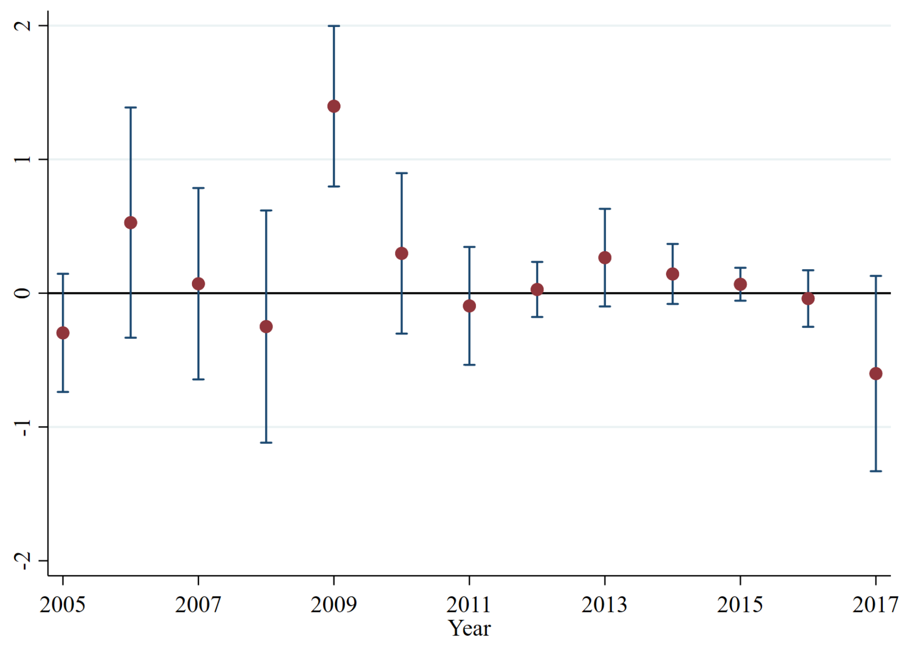
Figure A6 reveals that climate risk has the strongest effect in 2009, the last year of the recession that followed the financial crisis, for both long-maturity and short-maturity bonds. For long-maturity bonds, the climate risk coefficient is significantly negative in 2011 and positive in 2017. None of the other years exhibit a significant correlation between climate risk and borrowing costs. These patterns suggest that bond issuers in climate-exposed counties were differentially affected by the sharp economic downturn in 2009 but otherwise have similar borrowing costs to non-climate-exposed issuers.

Figure A6: Effect of Climate Risk on Municipal Borrowing Costs by Year

Panel A: Maximum Maturity over 25 Years



Panel B: Maximum Maturity under 25 Years



Note: This figure plots the year-by-year effect of climate risk exposure on the total annualized cost of new issue municipal bonds, using data from Painter (2020). The coefficients come from the same regression as in Table 3 of Painter (2020), with the climate risk measure interacted with dummies for each calendar year to obtain yearly coefficient estimates. 95% confidence bands are based on standard errors clustered by county. For ease of presentation, we exclude 2004 from the plot because of its wide confidence band.

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