Sea Level Rise Exposure and Municipal Bond Yields*

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Abstract

Coinciding with upward revisions of sea level rise (SLR) projections, municipal bond markets begin pricing increased risk of SLR exposure in 2013. The effect is larger for long-maturity bonds and is not solely driven by near-term flood risk. We apply a structural model of credit risk to quantify the implied economic impact and distinguish the effects of underlying asset values and uncertainty. The SLR exposure premium exhibits a different trend than house prices and is unaffected by controlling for them, which suggests that uncertainty about SLR's future impact, rather than reduced current asset values, drives the effect on bond prices.

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Over the past two decades, popular interest in climate change has increased dramatically as scientific forecasts have become more dire. One consequence of a warming climate is sea level rise (SLR). Since the Intergovernmental Panel on Climate Change (IPCC) report in 2007, scientists have increased SLR projections fourfold, with current upper-bound projections of 2.5 meters (8.2 feet) 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. In light of this, policymakers in the U.S. and abroad have begun to invest in relocation programs, raising questions about how long at-risk coastal communities will continue to be redeveloped. Estimating the economic impact of SLR exposure and when it will manifest is important for assessing the potential benefits of climate remediation, which 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, an ideal setting for assessing investors' expectations of the impact of climate risk on local economies. This is because the sources of repayment for municipal bonds are tied to local economic conditions, especially so for the school district bonds that comprise our sample, which are commonly backed by local real estate taxes. Although municipal bonds typically have maturities of less than 20 years, forward-looking behavior by coastal residents (e.g., relocation) may lead to economic damages well in advance of SLR-induced inundation. Since municipal bond prices reflect the likelihood that local government cash flows will be insufficient to make debt payments, this market provides 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 that trade in the same time period but vary in their exposure to SLR risk. The second challenge is to translate estimated changes in credit spreads into 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 document a trend toward pricing SLR exposure in the municipal bond market that begins around 2011. By 2013, there is a statistically significant SLR exposure premium in municipal bond yields. The emergence of this premium closely tracks the evolution of scientific forecasts and popular interest in SLR. We estimate that a one standard deviation (approximately ten percentage point) increase in the fraction of properties exposed to six feet of sea level rise is accompanied by a 5.3 basis point (bp) increase in municipal bond credit spreads in 2015, equivalent to 9% of the average spread in our sample. The 95% confidence interval associated with this estimate can rule out effects smaller than 2.7 bp or larger than 7.9 bp, and the estimates from 2014 to 2017 are statistically indistinguishable from it. For context, this effect is similar in magnitude to the difference in municipal bond yields between states that allow municipal bankruptcy relative to states that do not (Gao, Lee, and Murphy (2019)).

To interpret the economic magnitude of our findings, we adapt the Merton (1974) model of credit risk to the municipal bond market. 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 the estimated 5.3 bp SLR exposure premium (and the confidence interval surrounding it) is consistent with a reduction of 2.4% to 5.6% (1.3% to 8.1%) in the present value of the underlying cash flow stream, a proportional increase of 1.6% to 2.9% (0.8% to 4.2%) in the volatility of cash flows, or some combination of these effects, depending on the issuer's financial leverage. We consider a wide range of leverage ratios in the calibration to ensure our inability to observe issuer leverage ratios does not affect our conclusions. The estimated effects of SLR exposure on bond yields do not imply the expectation of catastrophic losses from climate-induced default in the municipal bond market, but they do suggest that investors anticipate a material economic impact of SLR risk on exposed municipalities.

To narrow the interpretation, we incorporate data on house prices as a proxy for underlying asset values. We find that, while house prices correlate with municipal credit spreads in an intuitive way, including the control does not change our main regression estimate. Moreover, when we aggregate house prices to the school-district level, we find a statistically insignificant effect of SLR exposure since 2004 and no discernible time-series pattern, in contrast to prior research finding a negative effect on individual house prices (e.g., Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020)). This suggests that property-level effects of SLR exposure do not aggregate to affect broader coastal real estate markets in our sample period. Assuming house prices are a valid control for the present value of municipal cash flows, this suggests that uncertainty about future municipal cash flows is the most likely driver of the SLR exposure premium. Further bolstering this interpretation, we show that dispersion in scientific projections of SLR is a stronger predictor of increases in the SLR premium than the median projection.[1]

To the extent that climate change is a salient risk to bondholders, the effect should be largest in longer-maturity bonds. This is true regardless of the precise nature of the risk (e.g., migration due to expected inundation, worsening storm intensity). Splitting the sample into long- and short-maturity bonds, we find that a positive relation between exposure and municipal credit spreads emerges across the maturity spectrum in the latter years of our sample. However, a within-district comparison reveals that the effect on credit spreads is significantly larger for long-maturity bonds.

At the district level, SLR exposure is highly correlated with storm surge risk. If SLR exposure proxies for hurricane risk, then our results are consistent with investors pricing a near-term increase in storm frequency and intensity instead of exposure to long-run SLR. Adding controls for storm surge risk helps to disentangle these explanations. The decomposition is inconclusive as to whether storm surge or SLR risks drive the premium for short-maturity bonds, but it shows that the credit spread premium after 2012 is primarily attributable to long-run SLR risk at long maturities and in the full sample.

In a set of auxiliary tests, we explore how state-level differences in local taxation, concern about climate change, and support for distressed municipalities influence the estimated SLR exposure premium. Intuitively, the SLR exposure premium is larger for bonds whose school districts rely more on local property taxes for budgetary needs and smaller for bonds whose districts rely more on state-level funding. We also find that the premium is larger in states where residents report higher levels of concern about climate change. This finding is consistent with existing literature showing that an area's beliefs about climate change affect how SLR exposure is priced in real estate markets (e.g., Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis

[1]We cannot rule out that rising attention to climate risk also plays a role in the price effects we observe. For survey evidence on household attention, see https://www.pewresearch.org/fact-tank/2020/04/21/how-americans-see-climate-change-and-the-environment-in-7-charts/.

(2020)). Finally, we show that our estimates are not driven by state-level policies on municipal distress (Gao, Lee, and Murphy (2019)); in fact, the estimated SLR premium would likely be larger in the absence of state support for distressed municipalities. Taken together, these findings suggest a role for statewide risk-sharing to support areas exposed to climate change, especially in states where residents are concerned about this risk.

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, Kiku, and Ochoa (2016), Berkman, Jona, and Soderstrom (2021), Hong, Li, and Xu (2019)) and their cost of capital (e.g., Sharfman and Fernando (2008), Chava (2014), Delis, de Greiff, and Ongena (2021)), as well as their operating performance (e.g., Barrot and Sauvagnat (2016), Addoum, Ng, and Ortiz Bobea (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, Gustafson, and Ivanov (2021)) and the beliefs of institutional investors (Krueger, Sautner, and Starks (2020)). Baker et al. (2018), Flammer (2021, Forthcoming), and Larcker and Watts (2020) study the pricing of "green" bonds issued to fund environmentally friendly projects. Giglio, Maggiori, and Stroebel (2014) and Giglio et al. (2021) 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 at both short and long horizons.

Our findings build on prior work, including Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020), that shows a negative effect of SLR exposure on residential real estate prices. These studies identify the effect of SLR exposure by comparing observably similar properties in close proximity to each other, so they do not address the question of how SLR risk affects the broader economy in coastal areas. Our evidence suggests that uncertainty about SLR's future impact and associated downside risks, rather than reductions in asset values, is affecting local economies today.[2] This is a unique finding in the climate finance literature and highlights

[2]Another distinguishing factor is that 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. Our examination of municipal bonds sheds light on the expected economic impact of SLR exposure as perceived by financial market participants who can diversify away from location-specific flood risk.

a benefit of studying municipal bonds, which are exposed to downside risk in local economies, rather than house prices, which are exposed to both downside risk and upside potential.

Another contribution of this paper is to adapt a structural model of credit risk from the corporate finance literature to the municipal bond market. The model highlights the joint roles of asset values and cash flow volatility in affecting bond prices and allows us to quantify the economic impact implied by our bond pricing estimates. Our calibration approach is straightforward to apply in other non-standard settings where 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.[3]

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 flood risk. The first important difference between our findings and those in Painter (2020) is with respect to magnitude. Painter (2020) estimates a 23.4 bp increase in long-maturity bond yields in response to a one percent increase in flood risk, measured by Hallegatte et al. (2013) as the annual GDP loss due to 40 centimeters (1.3 feet) of sea level rise.[4] Our structural model suggests that this 23.4 bp estimate implies substantially more economic damage than implied by Hallegatte et al. (2013), on the order of a 25% reduction in the present value of the cash flows backing bond repayment.

The timing of our estimated effects also differs from Painter (2020). We find an insignificant effect of SLR exposure on municipal bond spreads through 2012 and a positive effect afterwards. This pattern aligns with rising SLR projections and awareness. Painter (2020) finds that municipal bond markets began pricing flood risk in 2007, but does not provide year-by-year estimates. In the Internet Appendix, we present a replication analysis using the sample from Painter (2020) that

[3] In a recent working paper, Boyer (2020) adapts the Merton (1974) model to the municipal bond market. Our applications differ in two ways. First, we use the model to quantify the effect of economic shocks on bond yields, while Boyer (2020) uses the model to generate qualitative predictions regarding the effect of pension liabilities on debt prices. Second, we show how to apply the model to issuers without balance sheet information, whereas Boyer (2020) focuses on state-level issuers for which balance sheet data are available.

[4] In contrast to our measurement of SLR exposure at the school district level, Painter (2020) uses a measure of flood 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).

reveals his estimates are largest in 2009, immediately after the financial crisis. After the end of the Great Recession, the effect of flood risk on borrowing costs declines in magnitude and becomes statistically insignificant. This suggests that the yield premium in Painter (2020) may be driven by exposure to the Great Recession instead of changes in investor perceptions of climate risk.

From a policy standpoint, the 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 in both the near- and long-term. In contrast, the evidence in Painter (2020) suggests that remediation efforts would only have very long-term effects and that the expected benefits have declined since 2009, in contrast to the evolution of scientific consensus toward greater 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 interprets the estimates using a structural model of credit risk and supplementary analyses of real estate values, local tax regimes, and investor beliefs. Section 5 concludes.

1 Background

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. It is widely recognized that the 20th century saw the oceans rise by 1-2 millimeters per year. Disagreement arises when translating these past trends into future projections. In its 2007 report, the Intergovernmental Panel on Climate Change (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, 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, Aagaard, and Kuijpers (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 studies that project global average SLR through 2100. We use this panel to measure variation in global sea level rise projections over our sample period. The sample of studies and the selection criteria are described in Internet Appendix Section A1.

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. The shift in projections begins in 2007, with the best-case (1st percentile) scenario moving up sharply. The worst-case scenario forecasts increase significantly beginning in 2012, when the 99th percentile of sea level rise projections jumped 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. Changes over time in this figure suggest two sources of risk: increasing levels of predicted SLR, even in the most optimistic cases; and significantly more uncertainty. 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.[5]

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 term "sea level rise" from 2004, when data become available, until the end of our sample in 2017. This figure reveals steadily increasing interest in climate-related search terms over our sample period.

1.2 Risks to Municipal Bond Investors

SLR exposure creates multiple types of risks for exposed areas. In the long-run, rising oceans may inundate coastal properties, a major risk for the health of coastal economies. In the near-term, the warming climate has increased the projected severity of tropical storms and hurricanes. 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-

[5]This figure is based on both medium- and high-emissions scenarios. When focusing on high-emissions scenarios only, the 99th percentile is over six feet by the end of our sample period.

75). Importantly, regardless of whether long- or short-run inundation risk is being priced, the forward-looking nature of markets and local residents means that economic damages may be felt long before severe inundation manifests.

Short-term economic risks can be realized in a number of ways. The municipal bonds we examine are supported primarily by local property tax revenues. Not only does recent evidence suggest that local property prices have begun to reflect the long-run risks associated with sea level rise exposure (e.g., Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020)), but there is also downside risk to local economic activity more generally. When agents are forward-looking, economic impacts will occur prior to damages directly attributable to inundation. A growing body of anecdotal evidence shows that economic activity is moving away from SLR exposed areas in advance of flooding that is predicted to worsen over the coming decades. For example, Indonesia, the world's fourth most populous country, plans to spend $33 billion to move its capital from Jakarta to the less exposed island of Borneo.[6] In the U.S., the Federal Emergency Management Agency (FEMA) and the Department of Housing and Urban Development (HUD) have set aside billions of dollars for community relocation programs. There are already examples of residents being encouraged to relocate after storms due to the futility of reconstruction in the face of growing flood risks.[7] With exposed areas increasingly subjected to tidal flooding, municipal bondholders face the risk that the cash flows backing repayment will evaporate if residents of an exposed municipality decide to relocate.

We take a markets-based approach to analyzing the effect of SLR exposure on municipal credit spreads, and in turn coastal economies. All else equal, we expect higher SLR exposure to lead to higher municipal credit spreads due to a heightened risk of value-destructive flooding and associated reductions 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.

Our main empirical prediction is agnostic as to what type of inundation risk affects munici-

[6] "Indonesia will relocate capital from sinking Jakarta to Borneo," CBS News, August 27, 2019 (Link).

[7] "U.S. flood strategy shifts to 'unavoidable' relocation of entire neighborhoods," New York Times, August 26, 2020 (Link). See also "Climate Change is Bankrupting America's Small Towns," New York Times, September 2, 2021 (Link).

pal bond yields and through what channels. The forward-looking nature of bond investors and the potential for economic damages to precede inundation raises the possibility that bonds of all maturities will be impacted. However, we expect longer-maturity bonds to be more impacted because both short- and long-run risks are expected to increase as global temperatures rise over the coming decades.

More generally, the type of flooding that affects municipal bond spreads is informative with respect to the risks that concern investors. If investors are concerned about more severe storms, then measures of short-term flood risk should have more predictive power. If instead they are concerned about long-run inundation by rising oceans, then measures of long-run SLR exposure should matter more. We test distinguish these risks empirically by including measures of SLR and storm surge exposure in the same regression and comparing the coefficient estimates.

Both risks are mitigated to the extent that school district bonds are supported by higher levels of government. In these cases, school district bondholders are protected even if cash flows linked to the local economy and property values deteriorate in SLR-exposed districts. Thus, we expect municipal bond yields to be less sensitive, or in extreme cases insensitive, to district-level SLR exposure when the bonds are linked to a higher level of government.

While our main estimation approach is agnostic to exactly what economic forces affect the bond yields, a natural question is exactly how much of our results are driven by the effects of SLR on house prices (e.g., Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020)). In Section 4, we delve more deeply into how to interpret the overall estimates of the SLR exposure premium using a model-based approach and highlight how SLR's impact on housing affects the pricing of bonds backed by property tax revenues.

2 Data

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, 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. Second, much of the funding for public schools in the U.S. comes from taxes on local real estate, so there is a direct link between school districts' ability to repay debts and the anticipated effects of SLR on local economies. Third, 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. We explain why this level of granularity is critical to our identification strategy in Section 3.1.

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 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 transaction yields are especially noisy (Green, Hollifield, and Schurhoff (2007)).[8] We do not impose any restriction on the type of bond issued, as the vast majority of school districts issue general obligation bonds.

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. 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.

We restrict the sample to coastal watershed counties, as defined by the National Oceanic and Atmospheric Administration (NOAA), in states with an ocean shoreline.[9] Our process to determine the SLR exposure for each school district bond issuer in coastal counties closely follows Bernstein, Gustafson, and Lewis (2019). First, we identify the location of each residential dwelling in the school district using the real estate assessor and transaction files in the Zillow Transaction and Assessment Dataset (ZTRAX). We then determine each property's SLR exposure using the

[8]Internet Appendix Table A3 shows that our main results are robust to including the initial months of trading. The regression coefficients are quantitatively similar and statistically significant, but less precisely estimated.

[9]See https://coast.noaa.gov/htdata/SocioEconomic/NOAA_CoastalCountyDefinitions.pdf.

NOAA SLR viewer (Marcy et al. (2011)). Importantly, the NOAA's calculations account for tidal variation and other geographic factors that affect the impact of global oceanic volume increases on local SLR.[10]

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, while the light blue area represents the exposure to 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 district boundaries.

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. For example, to calculate the district-level exposure to six feet of SLR, we count all dots within the blue and green areas and divide by the total number of dots in a district to obtain the fraction of exposed properties. We use the state and name of each school district to link the geographic exposure information to municipal bond issuers.[11] After merging the panel of bond yields with measures of SLR exposure, the sample consists of 564,095 bond-month observations of 59,380 bonds issued by 1,508 school districts.

To ensure uniformity over the sample period and to facilitate the estimation of panel regressions with county-time fixed effects, we impose a "balanced panel" restriction on our data. Specifically, we require that each county has more than one school district bond issuer and that each

[10]Murfin and Spiegel (2020) argue that this exposure measure does not account for subsidence, so it 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" (https://coast.noaa.gov/data/digitalcoast/pdf/slr-faq.pdf). In other words, the NOAA measure is based on more predictable and better understood factors, but may miss some less predictable aspects of SLR exposure. The relative sea level rise (RSLR) measure proposed by Murfin and Spiegel (2020) could capture missing factors and represent SLR risk more accurately. Alternatively, it could introduce noise, as suggested by the NOAA, and may not represent investors' information sets because it is not easily accessible through public means. To address this issue, we construct a measure of RSLR exposure and present quantitatively similar bond pricing results in Internet Appendix Table A2 and Figure A1. The similarity is due to the high correlation between RSLR and SLR exposure at the district level ($\rho = 0.97$), despite an imperfect correlation between RSLR and SLR at the house level ($\rho = 0.77$). We observe a small decrease in the coefficient estimate, consistent with RSLR introducing measurement error and attenuation bias, but the difference is statistically insignificant.

[11]The name matching proceeds in multiple steps. First, we clean and standardize the format of 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.

district has at least one secondary market bond price observation per year. This restriction excludes Florida because its school bonds are issued at the county level, so we are unable to identify within-county effects of SLR exposure. In the next section, we describe our regression framework and provide out-of-sample evidence highlighting the importance of within-county variation for our identification strategy. The "balanced panel" restriction reduces the sample to 321,735 bond-month observations of 31,352 bonds issued by 373 districts.[12]

Finally, given that the link between local property values and the cash flows supporting repayment of school bonds is central to our predictions, we exclude California from our main sample and analyze it separately because its school districts are insulated from this economic mechanism. Specifically, the impact of SLR on the creditworthiness of California school districts is dampened by Proposition 13, which caps property tax rates as a percentage of assessed value and the rate of assessment changes.[13] As a result, California property taxes are inflexible in both directions, with reductions only possible after a house is enrolled in Proposition 8 reform, which subjects it to market value adjustments.[14]

After applying these restrictions, the sample consists of 175,415 bond-month observations of 18,366 bonds issued by 238 school districts. There are 18 states in the unrestricted sample but only 11 in the restricted sample. To ensure that the distribution of observations across states is not driving our results, we replicate our main results in Internet Appendix Table A5 using weighted regressions in which each state is equally represented.

Table 1 summarizes the variables used in our main analysis. About 46% of our observations are from districts that would experience at least some chronic inundation after six feet of global average SLR. On average, 7% of properties are exposed at the six-foot level in these districts. The average municipal bond-month observation in our sample has a yield of 3.24%, which is 57 bp over the AAA-rated benchmark curve. It has ten years to maturity, has aged four years since

[12] Internet Appendix Table A4 shows that our main results are robust to using the full "unbalanced" panel of bond-month observations. Those results still do not incorporate variation from Florida because our main regression specification includes county-year-month fixed effects.

[13] Wasi and White (2005) show that assessed property values in California have not kept pace with market prices, resulting in subsidies of thousands of dollars per year for coastal homeowners.

[14] In addition, California has a state-level organization, the California School Finance Authority (CSFA), that provides access to bond financing through a statewide conduit facility, the Qualified Public Educational Facility Bond Pool (QPEFBP), as well as short-term financing for distressed districts through the Tax and Revenue Anticipation Note (TRAN) program. These risk-sharing mechanisms are similar in spirit to the proactive policies for distressed municipalities pursued by other states (Gao, Lee, and Murphy (2019)), which we examine in Section 4.3.3.

issuance, and has $543,000 of monthly trading volume (conditional on non-zero trade). We find little unconditional difference in these characteristics between the exposed and full sample. After winsorizing at the 1% level, municipal bond credit spreads range from -19 bp to 261 bp 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 Effect of SLR Exposure on Municipal Bond Yields

3.1 Identification Strategy

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 of SLR over our sample period. To test this hypothesis, we estimate the following regression:

$$\text{Spread}_{bijt} = c_{jt} + c_i + \sum_{y=2002}^{2017} 1\left(\text{Year} = y\right)\left[\alpha_y \text{SLR Exposure}_i + \theta_y Z_{bijt}\right] + \gamma X_{bijt} + \epsilon_{bijt}, \tag{1}$$

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 a one standard deviation change in the fraction of SLR exposed properties in district i. These coefficients are estimated relative to the baseline effect in 2007, which we omit from the yearly coefficients.

Following Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020), we use six-foot SLR exposure as our primary measure of SLR risk. By the end of our sample period, most high-emissions scenarios project a 99th percentile of SLR exceeding six feet by the end of the century. 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.

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 so 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 above, the mean (median) number of districts with bonds trading in a county-year-month is 3.6 (2).

Figure 4 provides evidence on the endogeneity bias that could emerge without controls for local economic conditions. Following Bernstein, Gustafson, and Lewis (2019), we plot the non-parametric relation between SLR exposure deciles and home prices, using geographic areas with zero SLR exposure as the benchmark group. Panel A measures exposure at the county level and controls for state-year fixed effects. This specification reveals a positive and significant relation between SLR exposure and home prices, which suggests that within a state, SLR exposure is positively correlated with local economic conditions. Thus, a county-level regression of bond yields on SLR exposure that controls for state-time effects would likely be affected by omitted economic features. Panel B measures SLR exposure at the school district level and includes county-year fixed effects. This panel shows an insignificant relation between house prices and SLR risk after the inclusion of more granular geographic controls, indicating that within a county, variation in SLR exposure is uncorrelated with local real estate market conditions. This highlights the importance of controlling for county-year fixed effects in our analysis to absorb time-varying local economic factors that would be correlated with SLR at higher levels of geographic aggregation.

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 credit spreads. This 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 credit spreads emerges or increases as SLR projections worsen, it is unlikely that the relation we observe is driven by omitted factors.

In addition to issuer and county-year-month fixed effects, our regression analysis controls for the term structure, illiquidity, and other features of municipal bonds.[15] The yearly coefficients on Z_{bijt} control for time-varying factors including the term structure of credit spreads, the issuer's option to call bonds before maturity, and the value of bond insurance (Cornaggia, Hund, and Nguyen (2021)). Other control variables X_{bijt} include the district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues.

[15] We do not control for the tax status of the bond because our sample only includes tax-exempt bonds and the location-time fixed effects in our regressions account for time-varying state income tax rates.

3.2 Main Estimate of the SLR Exposure Premium

Table 2 presents estimates of how SLR 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 exceeding five feet of end-of-century SLR.

Our main prediction 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. We include county-year-month fixed effects to control for time-varying local economic conditions, meaning that the SLR exposure coefficients are identified from differences in the credit spreads of bonds issued by districts in the same county, trading in the same month. The baseline value of SLR exposure estimates the effect in 2007 in column (1), so the other yearly coefficients reflect the effect of SLR exposure relative to 2007. We incrementally add issuer fixed effects in column (2) and bond-level controls in column (3). Notably, in column (1) we see that SLR Exposure has a baseline *negative* effect on spreads, consistent with issuers nearer to the coast having confounding features (e.g., higher real estate values) that could lower credit spreads.

We find little evidence that the relation between SLR exposure and municipal bond credit spreads changed between 2001 and 2010. After 2010, the coefficients become consistently positive, indicating that municipal bond credit spreads are higher in exposed relative to unexposed areas in the latter part of our sample, compared to the base year of 2007. From 2011 to 2013 the coefficients are all positive and mostly between 1.8 and 2.3. Between 2014 and the end of the sample in 2017, the coefficients become more statistically significant and range from 3.9 to 5.9 across the three columns, implying that a one standard deviation increase in SLR exposure corresponds to a 3.9 bp to 5.9 bp increase in municipal credit spreads. Compared to the average spread of 57 bp, these estimates suggest that a one standard deviation in SLR exposure results in a 7% to 10% increase in municipal bond spreads by the end of our sample period.

Figure 5 provides a visual depiction of the specification in column (3). The figure reveals a generally increasing trend in the SLR exposure premium since 2010, with the premium becoming statistically significant in 2013 and more significant in 2014, after which the coefficient estimates are statistically indistinguishable from each other. This rise in the SLR exposure premium around 2014 coincides with the evidence in Figure 1, which shows a jump in SLR projections in the scientific community beginning in 2013. The figure also reveals no significant SLR exposure premium earlier in our sample. This result differs from the claim in Painter (2020) that the municipal bond market was pricing SLR risk beginning in the second half of 2007.[16]

Internet Appendix Table A5 provides 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, 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 four feet instead of six feet of global sea level rise.

3.3 Long- versus Short-Run Risks

We now consider whether the long- or short- run risk channels discussed in Section 1.2 are likely drivers of the SLR exposure premium. We begin by examining whether the SLR exposure premium relates to bond maturity. To better understand the underlying climate risks, we then distinguish between exposure to storm surges, a short-term risk, and sea level rise, a long-term risk.

Although bonds of all maturities may be influenced by SLR exposure, we expect long-maturity bonds to be impacted at least as much as short-maturity bonds. To assess differences across the maturity spectrum, in columns (1) and (2) of Table 3 we partition the sample on whether a bond's maturity is less than or greater than ten years. Approximately 42% of bond-month observations have more than ten years to maturity. To parsimoniously examine how the evolution of the SLR exposure premium varies by bond maturity, we create a Post indicator that equals one for observations after 2012 and interact that with SLR exposure. Columns (1) and (2) indicate that the post-2012 SLR exposure premium is statistically significant and of similar magnitude for short-

[16] Although we use different data and a different measure of exposure in our analysis, we provide evidence in the Internet Appendix based on the sample of new issues from Painter (2020). We show that the yield effects estimated by Painter (2020) are concentrated around the financial crisis and either negative or statistically insignificant in each year from 2010 to 2016.

and long-maturity bonds.[17]

As we explain in Section 1.2, the SLR exposure premium in short-maturity bonds could be driven by either short- or long-run inundation risks. In either case, we expect the premium to be increasing in the bond's maturity. Column (3) examines this prediction by adding district-year-month fixed effects so that we compare bonds with different maturities, issued by the same school district and traded in the same month. The explanatory variable of interest is the triple interaction between SLR exposure, the post-2012 period, and the logarithm of time to maturity. Consistent with both the long- and short-run risk mechanisms, 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.

To distinguish between long- and short-run flood risks, we introduce a measure of short-term flood risk in the form of storm surge exposure. While SLR exposure only affects flood risk in the very long-run, more frequent and intense storms could have both short- and long-run effects. We collect property-level data on storm surge exposure using the NOAA Sea, Lake and Overland Surges from Hurricanes (SLOSH) model. To develop this model, the NOAA simulates 100,000 Category 3 hurricanes for each coastal water basin and estimates the maximum storm surge height for every point along the coast in a high resolution spatial image file (raster).[18]

Table 4 augments the main regression with this measure of storm surge exposure. Column (1) is based on the full sample, while columns (2) and (3) are based on the long- and short-maturity samples defined above. For the full sample, the SLR exposure interaction with the post-2012 indicator is statistically significant, while the storm surge interaction is not. Column (2) reports a similar result for long-maturity bonds. Column (3) reveals a less conclusive picture for short-maturity bonds, as both interaction coefficients are positive, with similar magnitude, but statistically insignificant. One caveat regarding the partitioned analyses in columns (2) and (3) is that we may

[17] Internet Appendix Table A6 shows that the estimates in Table 3 are robust to earlier thresholds for the Post indicator (2009, 2010, or 2011 instead of 2012) but become less statistically significant for later thresholds (2013 or 2014) due to a reduction in post-treatment observations.

[18] The process of mapping NOAA storm surge exposure to school districts mirrors that for SLR. We first measure the property-level storm surge using the raster based files available at NOAA. See `https://www.nhc.noaa.gov/nationalsurge/`. We run a non-interpolated raster sample at the property centroid to estimate property-level storm surge values. We then average this property-level measure across all properties in each school district to get the average number of feet of inundation if a Category 3 hurricane were to hit the district. Storm surge and SLR exposure are strongly positively correlated ($\rho = 0.83$). Differences between the measures depend on local geography. For instance, areas on either side of a peninsula could have similar SLR exposure but different storm surge exposure due to differences in exposure to hurricane-force winds.

not have enough statistical power to separately identify the effects of SLR exposure and storm surge, which are highly correlated.

The main takeaway from Table 4 is that SLR exposure, a proxy for long-run flood risk, appears to be a more important driver of the SLR exposure premium than storm surge exposure, which has both short- and long-run effects. However, this conclusion applies mostly to long-maturity bonds. More statistical power is needed to determine the relative importance of short- and long-run risks in driving the observed effects on short-maturity bond spreads.

4 Interpreting the SLR Exposure Premium

This section provides a theoretical framework and additional empirical evidence to provide an economic interpretation of the SLR exposure premium. First, we present a structural model of municipal credit risk based on Merton (1974), which shows that higher municipal bond spreads could be due to reduced underlying asset values (e.g., real estate prices) or an increase in the volatility of future cash flows (i.e., downside risk). The model allows us to quantify the economic impact implied by the estimated SLR premium in terms of these parameters. Next, we present evidence on residential real estate prices and dispersion in SLR forecasts that suggests the pricing of SLR risk reflects heightened uncertainty rather than reduced asset values. Finally, we consider several economic mechanisms that could mediate the effect of SLR exposure on bond spreads, including investor beliefs, the local tax regime, and state-level policies on municipal distress.

4.1 Structural Model of Municipal Credit Risk

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

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

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 the same as in the corporate context. The source of debt repayment is a cash flow stream that depends on tax revenues, expen-

[19] 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.

ditures, and intergovernmental transfers. The present value of cash flows, which we call the asset value, is equivalent to the market value of a firm in the discounted cash flow framework.[19]

Suppose 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 the underlying assets and a short call option on the assets struck at the bond's face value. Under this basic setup, the value of the bond is

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

where

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

We compute a bond's credit spread as the difference between its yield-to-maturity, which can be expressed as $y = \frac{1}{T}\ln(K/B)$, and the risk-free rate. Most municipal bonds pay coupons that are exempt from income taxation, so we use a tax-exempt risk-free rate for our calibration.[20]

The option-pricing intuition behind the model implies that the higher yields of SLR exposed bonds at the end of the sample are either due to lower V, the present value of cash flows (e.g., due to lower property taxes), or higher σ, reflecting uncertainty about future cash flows. The latter channel distinguishes this paper from studies of climate risk and home prices (e.g., Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020)), which focus on the former channel at a finer level of granularity (individual houses). However, we require additional evidence to disentangle these channels, which we present in Section 4.2. In the remainder of this section, we use the model to quantify the changes in V or σ that could explain the SLR premium.

Before proceeding, we should provide some context for this exercise. With few exceptions (e.g., Gray, Merton, and Bodie (2007), Boyer (2020)), structural models of credit risk have not been applied to government debt markets. However, the intuition of the model is the same as in the corporate setting. Following Schaefer and Strebulaev (2008), we can think of a bond's value as

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. We discuss state-level policies regarding the resolution of municipal distress in Section 4.3.3.

[20]The Merton (1974) framework 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 Internet Appendix Section A4.1, we obtain quantitatively similar estimates performing the model analysis on tax-adjusted yields as in Schwert (2017), with the interest rate swap curve as the risk-free benchmark.

consisting of credit and non-credit components:

$$D = D_C + D_{NC}. \tag{5}$$

Merton (1974) models the credit component, D_C, as dependent on the distribution of the present value of cash flows and the face value of debt that must be repaid in the future. The cash flow stream in the municipal context depends on local government tax revenues and expenditures, as well as conditional (e.g., bailouts) and unconditional transfer payments, which differentiates it from the usual notion of profits for a firm. Nevertheless, the default risk of a local government depends on the ability of these cash flows to sustain the repayment of debt, just as a firm relies on its current and future profits to repay its creditors.

The failure of structural models to match the observed yields of corporate bonds has been well documented (e.g., Huang and Huang (2012)). This is due to the existence of non-credit factors, D_{NC}, such as liquidity, that have a non-trivial effect on the pricing of debt. We anticipate that the Merton (1974) model would exhibit the same shortcomings in the municipal setting.

However, our objective is not to match the level of municipal bond yields, but rather to predict changes in yield as with respect to changes in the fundamentals governing repayment of the bond (i.e., the level and volatility of cash flows). In other words, we use the model to generate hedge ratios, which reflect the sensitivity of the bond value to the underlying asset value. This is equivalent to the hedge ratio of the credit component, D_C, because the non-credit component, D_{NC} is unrelated to credit risk, and therefore, to the asset value. Confirming this intuition, Schaefer and Strebulaev (2008) show that the Merton (1974) model provides accurate predictions of the empirical hedge ratios of corporate bonds, including high-investment-grade (e.g., AA-rated) bonds that have similar historical default rates to municipal bonds.[21]

In contrast to Schaefer and Strebulaev (2008), who study the relation between bond and equity returns, we use the model to interpret difference-in-differences regression estimates. Nevertheless, our approach is conceptually similar because we focus on the relation between changes in bond values and changes in fundamentals, as opposed to the mapping between the level of fundamentals and the level of yields. Our regression isolates the credit component of yield changes

[21] It is not possible to replicate the results in Schaefer and Strebulaev (2008) for municipal bonds because the estimation of empirical hedge ratios requires equity return data.

by controlling for liquidity proxies and time-varying county-level economic conditions.[22]

For empirical application of the model, we calibrate the yield change for a typical municipal bond following a change in the underlying asset value or cash flow volatility. Table 1 indicates that the mean bond in our sample has a yield-to-maturity of 3.24%, which corresponds to a credit spread of 56 bp over the maturity-matched AAA-rated tax-exempt benchmark rate of 2.68%. 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 $T = 7.5$, $r = 2.68\%$, and $y = 3.24\%$ for our calibration.[23]

Data on the capital structure and cash flows of municipal issuers are difficult to obtain and it is impossible to observe the market value of the expected cash flow stream. Therefore, we take a flexible approach, calibrating the model to a wide range of leverage ratios (K/V in the model) and asset volatilities (σ) to match the calibrated bond yield. 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 6 shows that the implied volatility is decreasing in leverage.

We use these parameter values to compute the model-implied effects of changes in the present value of cash flows or their volatility on the yield-to-maturity of a municipal bond. Panels A and B of Figure 7 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. 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.[24]

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 bp, while a 10% drop in asset value raises yields by 10.8 bp. Under the same specification,

[22]Although we examine the term structure of municipal bond spreads in our regression analysis, we avoid this issue in the structural model because prior research (e.g., Eom, Helwege, and Huang (2004)) suggests it performs poorly at capturing term structure effects. This is in part due to the model's parsimonious specification of interest rate dynamics.

[23]In Internet Appendix Sections A4.2 and A4.3, we report model-implied changes in yield based on alternative specifications with bankruptcy costs and senior debt, respectively. These results suggest that our conclusions are robust to model specification and the possible presence of bank loans on the issuer's balance sheet (Ivanov and Zimmermann (2021)).

[24]If the estimated SLR premium is due to a reduction in the present value of cash flows, this could be due to changes in expected cash flows or by movements in discount rates. Although the model does not distinguish between these channels, we argue that changes in expected cash flows would be more plausible than changes in discount rates. Recall that our empirical estimates are from a difference-in-differences regression framework that compares the credit spreads of exposed and unexposed issuers in the same county. Thus, systematic risk needs to have increased differentially for exposed issuers relative to the start of the sample period for discount rates to explain our findings.

increases in volatility of 1% and 10% correspond to yield increases of 3.6 bp and 41 bp, 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 bp and 27 bp, respectively, while increases in volatility of 1% and 10% correspond to yield increases of 2.0 bp and 21 bp.

Panel C of Figure 7 presents the combination of asset value and volatility shocks that correspond to the estimated 5.3 bp increase in municipal bond yields associated with one standard deviation higher SLR exposure in 2015 (Table 2, column (3)). This estimate is in line with a reduction of 2.4% to 5.6% in the present value of the underlying cash flow stream or a proportional increase of 1.6% to 2.9% in the volatility of cash flows, depending on the issuer's leverage and corresponding implied volatility. Naturally, a larger shock to asset value implies a smaller shock to volatility, and vice versa, holding the change in yield fixed. Taking statistical uncertainty in our estimate into account, the 95% confidence interval (2.7 bp to 7.9 bp) corresponds to asset value reductions from 1.3% to 8.1% or proportional volatility increases from 0.8% to 4.2%.

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 bp increase in annualized issuance costs for bond issues with a maximum maturity of 25 years or longer. To calibrate the model, we use a sample of new issue municipal bonds from Mergent following the criteria in Painter (2020). 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%.

Panel D of Figure 7 depicts the combination of shocks to the asset value and volatility necessary to produce the Painter (2020) result. Without a shock to the volatility of cash flows, this change in yield corresponds to a reduction of 25% to 30% in the present value of cash flows. On the other hand, if the reduction in cash flows is on the order of 1%, then the implied increase in volatility is between 5% and 20%. 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 of climate risk, consistent with exposure to the Great Recession affecting the estimates.

While the estimates in Figure 7 are informative about the economic impact of SLR risk on exposed issuers, there is a wide range of possible effects that depend on whether SLR risk is primarily impacting current asset values or the volatility of future cash flows. In the next section, we provide auxiliary evidence to distinguish among these channels.

4.2 Evidence on Asset Values and Uncertainty

The model makes clear that the estimated relation between SLR exposure and municipal bond spreads could be driven by a decrease in the present value of municipal cash flows or an increase in uncertainty regarding those cash flows. Since the school district bonds in our sample are primarily backed by local property taxes, it is natural to examine residential real estate prices to assess whether reduced asset values can explain the SLR premium in municipal bonds. Indeed, Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020) find that SLR exposure has a negative impact on coastal home values in the second half of our sample period. However, the highly localized identification strategies employed by these studies, which compare individual properties in the same geographic area that are observably similar, preclude inference regarding the overall effect of SLR exposure on the value of real estate at the school-district level. Thus, we conduct tests using district-level house prices to clarify this issue.

If the effect of SLR exposure on bond spreads is due to lower house prices in exposed districts, then we should observe changes in our main coefficient as we include local house price controls in the regression (i.e., due to alleviated omitted variable bias). We test this approach in Table 5, which reports four specifications based on different methods of measuring house prices. One approach uses realized house price values from the ZTRAX dataset, which maps directly into the property valuations used for tax purposes. We restrict attention to school district-year observations with at least 50 house transactions recorded in ZTRAX to ensure a minimum level of data quality. Alternatively, we use the Zillow House Price index to capture the estimated prices of all homes (both sold and unsold), which avoids selection bias on houses that are sold in a given year. A last challenge that we address is capturing the correct functional form to fully account for potential omitted variable bias. We control for various points in the realized house price distribution to address this issue.

Column (1) of Table 5 reports our main specification (without house price controls) as a baseline measure of the SLR premium, with a one standard deviation increase in SLR exposure raising municipal bond yields by about 4 bp after 2012. Column (2) adds the logarithm of the annual median house price at the district level, using realized housing transactions. We see both a significant negative correlation between house prices and yields and a negligible change in the SLR effect on bond yields. Column (3) partitions each district's housing transactions into SLR exposed and unexposed properties and reveals similar patterns. To account for the fact that columns (2) and (3) are based on transaction prices, column (4) uses the Zillow House Price index, aggregating the zip-code-level index to the school-district level. Notably, the coefficient on this measure is similar in magnitude to column (2) but statistically insignificant. Finally, column (5) controls for the distribution of realized house prices using the 10th, 25th, 50th, 75th and 90th percentiles. Even after this flexible control for house prices, the SLR exposure coefficient is quantitatively similar to the baseline estimate.

The takeaway from Table 5 is that controlling for district-level house prices, which should be highly correlated with the present value of local property tax revenues, has a negligible effect on the SLR exposure premium. As before, we find that a one standard deviation increase in SLR exposure after 2012 results in an approximately 4 bp increase in bond spreads. Internet Appendix Figure A2 reports the year-by-year effect and reveals the same time-series pattern as Figure 5. Consistent with the intuition from the structural model, there is a statistically significant negative relation between house prices and municipal bond spreads, even after controlling for time-invariant district characteristics with fixed effects. However, this channel is distinct from the effect of SLR exposure on bond spreads.

This result is somewhat surprising based on the existing literature linking SLR exposure to coastal real estate prices, but it highlights the different levels of aggregation between our study and prior research on individual house prices. To shed further light on this difference, Figure 8 presents estimates of our main regression with the logarithm of annual median house prices as the dependent variable instead of the bond spread. This regression is similar in spirit to Panel B of Figure 4, but allows for time-varying coefficients and includes the controls from our bond pricing regression. After the first few years of the sample period, which show a negative effect of SLR exposure on district-level house prices, the yearly SLR exposure coefficients are statistically insignificant. The time-series pattern in Figure 8 stands in contrast to the upward trend in bond spread coefficients exhibited in Figure 5.

Overall, the evidence in Table 5 and Figure 8 suggests that the estimated SLR premium is not primarily driven by reductions in the value of real estate (and the present value of property taxes) in exposed school districts. Instead, the SLR premium appears to be due to heightened uncertainty regarding future cash flows in exposed school districts. This is a unique finding in the climate finance literature and highlights a benefit of studying municipal bonds, which are exposed to downside risk in local economies, rather than house prices, which are exposed to both downside risk and upside potential. Recalling the model estimates from the previous section, our main empirical estimate of the SLR exposure premium corresponds to a proportional increase of 1.3% to 2.3% in cash flow volatility in SLR-exposed districts after 2012.

To provide support for the role of uncertainty about SLR's impact in affecting bond spreads, we turn to the literature on SLR projections, discussed above in Section 1.1. Garner et al. (2018) note that "although central estimates of 21st century global-mean SLR have been relatively consistent, the range of projected SLR has varied greatly over time. Among studies providing multiple estimates, the range of upper projections shrank from 1.3–1.8 [meters] during the 1980s to 0.6–0.9 [meters] in 2007, before expanding again to 0.5–2.5 [meters] since 2013." We use projections from the studies surveyed by Garner et al. (2018) to exploit variation in the level and dispersion in projections over time. Each of these studies provides multiple estimates of potential end-of-century SLR that depend on scenarios related to global warming. For each study, we record the highest, lowest, and median estimate. Then we construct time-series measures of the median and range of scientific forecasts over rolling two-year windows.[25]

Table 6 uses these time-series measures of SLR forecasts in two ways. Columns (1) and (3) are based on the median and range of the fraction of properties in a school district that are exposed to SLR, computed using the annual median and range of projections.[26] Columns (2) and (4) use our baseline measure of SLR exposure, the standardized fraction of properties exposed to six feet of SLR, and interact it with the annual median and range of forecasts. The first two columns are

[25]Few scientific studies make claims about which scenarios are most likely, hence we focus on simple moments of the distribution of reported projections. Prior to 2008, the median and range of projections are constant because there are no studies projecting SLR between 2002 and 2006. Most of the studies in Garner et al. (2018) were published from 2007 onward, providing useful variation over the period when we observe the onset of bond pricing effects.

[26]To illustrate the calculation of these metrics, suppose the median projection in a year is two feet and the range is from one foot to five feet. Then the SLR Exposure Median is the fraction of properties exposed to two feet of SLR, while the SLR Exposure Range is the difference between the fractions of properties exposed to five feet and one foot of SLR.

based on all of the articles surveyed by Garner et al. (2018), while the latter two columns use a select set of articles following the procedure described in Internet Appendix Section A1.

Across all four columns, the range of forecasts has a positive and statistically significant coefficient, while the median is negative and marginally significant in columns (1) and (3) and statistically insignificant in columns (2) and (4). This analysis offers suggestive evidence that uncertainty regarding SLR, rather than the level of SLR forecasts, is driving municipal bond yields higher toward the end of our sample period. However, we should note that these time-series are positively correlated, making it difficult to disentangle them empirically.[27] Moreover, we cannot rule out that the timing of the SLR exposure premium's emergence is driven by increased awareness of climate change over our sample period.

4.3 Mediating Channels: Local Beliefs, Tax Reliance, and Distress Policies

In this section, we consider additional institutional and behavioral channels through which SLR exposure could impact bond yields. First, we use state-level segmentation in the municipal bond market to explore the role of investors' beliefs in the pricing of climate risk. Second, we examine the local tax regime, which determines how real economic shocks affect school district budgets. Finally, we discuss the role of state-level policies on municipal distress, which affect how local government funding shortfalls translate into creditor losses.

Before proceeding, we should explain how these channels affect the interpretation of the preceding empirical results. Our estimates of the SLR exposure premium, and the model-based quantification of the underlying economic impact, are based on the observation-weighted average effect in the sample. However, there is cross-sectional heterogeneity in this effect across states, some of which is attributable to the channels discussed below. The factors discussed in this section are not mutually exclusive. On the contrary, we observe a positive correlation between state-level beliefs about climate change, local tax regimes, and policies on municipal distress. Therefore, we encourage a cautious interpretation of our results and the following discussion.

4.3.1 Investor Beliefs

Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020) find that cli-

[27] SLR Exposure Range and SLR Exposure Median have a correlation of 0.75. Forecast Median and Forecast Range have a correlation of 0.46, while their interactions with SLR Exposure have a correlation of 0.95.

mate change beliefs affect how real estate markets price SLR exposure. It is reasonable to expect that differences in local beliefs also matter for municipal bond pricing because buyers are often local retail investors due to the tax advantages of in-state ownership (Schultz (2012)).

To measure an area's beliefs about climate change, we merge our data with the Yale Climate Opinion Maps (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 contains. 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.

In columns (1) and (2) of Table 7 we partition the 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, North Carolina, South Carolina, Mississippi, and Louisiana. The SLR exposure premium since 2013 is positive and statistically significant in states with an above-median level of worry. In less worried states, the SLR exposure premium actually goes in the opposite direction in the later part of our sample. In column (3) of Table 7 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 post-2012 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.

The evidence in Table 7 suggests a similar role for climate beliefs that prior researchers have observed in housing markets. However, this result complicates the interpretation of our main empirical estimates. As discussed above, our estimates reflect the observation-weighted average effect of SLR exposure in our sample. To the extent that the objective effect of SLR exposure on default risk differs from the beliefs of the investors driving our estimates, our conclusions on the economic impact of SLR may be biased.

4.3.2 Local Tax Regimes

As discussed in Section 2, local property taxes are the primary source of school funding in most places. This creates a direct link between future changes in real estate values and the cash flows available to repay school district bonds. Where districts are more dependent on property tax revenues, we expect to find a larger effect of district-level SLR exposure on bond yields.

Table 8 presents a test of this channel. In column (1) we interact SLR exposure with the post-2012 indicator and the average property tax rates for the state. We find that states with higher property tax rates exhibit larger credit spread increases in SLR-exposed districts. To address the concern that differences in tax rates do not reflect differences in dependence on property tax revenue, column (2) replaces property tax rates with the proportion of school funding coming from local sources. We find that school districts which are more reliant on local revenue streams have experienced larger increases in credit spreads associated with SLR exposure.[28]

A limitation of the preceding proxies for local revenue dependence is that even if property taxes make up the majority of the revenue base, school district budgets may be insensitive to local economic shocks. To examine this possibility we introduce data from California, which until this point we have excluded from our sample because of its low expected elasticity between local property values and municipal credit spreads. As noted previously, California is unique with respect to school funding because it has inelastic property tax revenues due to Proposition 13. Column (3) replicates our main analysis using California school districts and finds a statistically insignificant coefficient on SLR exposure after 2012. Thus, where there is a weak link between local property values and the cash flows backing bond repayment, we find no effect of SLR exposure on municipal bond spreads.

4.3.3 State Policies on Municipal Distress

Our findings suggest that SLR risk increases default risk, with investors pricing higher expected losses (i.e., higher default probability or lower expected recovery) for SLR exposed issuers toward the end of our sample period. Each state has its own policies on the ability of its municipalities to

[28]Property tax rates are from the Tax Foundation (https://files.taxfoundation.org/20200225111115/Facts-Figures-2020-How-Does-Your-State-Compare.pdf). Sources of school funding are from the Congressional Research Service (https://www.everycrsreport.com/reports/R45827.html).

default on their debt, which could have implications for the relation between SLR risk and municipal default risk. Gao, Lee, and Murphy (2019) categorize states as allowing municipalities to file for Chapter 9 bankruptcy (South Carolina and Texas, in our sample), having "proactive" policies that offer assistance to distressed municipalities while discouraging Chapter 9 bankruptcy (Maine, New Jersey, New York, and North Carolina), or lacking policies regarding financial distress (Connecticut, Louisiana, Massachusetts, Mississippi, and Rhode Island).[29] These authors show that proactive policies are associated with lower default rates, higher creditor recoveries, and lower credit spreads relative to the Chapter 9 approach. Thus, it is important to understand how these policies affect the pricing of SLR risk.

Table 9 partitions the sample according to the classification in Gao, Lee, and Murphy (2019) to assess how these policies correlate with the SLR exposure premium. Column (1) shows a slightly larger SLR premium in states with proactive distress policies relative to the full sample, while column (2) shows a statistically insignificant effect in Chapter 9 states. Column (3) shows a highly significant negative SLR premium in states with no explicit distress policies, though we should note that this group comprises only 3% of the sample observations. The final column includes an interaction effect confirming that the SLR premium is significantly larger in proactive states.

Considering the effect of proactive distress policies in isolation, it is surprising to see that the SLR exposure premium is concentrated states with proactive policies. However, the same states – New Jersey and New York, in particular – are more concerned about climate change and rely more on local property taxes to fund schools. The results in Table 9 suggest that these other mediating channels outweigh the effect of more supportive distress policies.

In the absence of state support, we would expect to see even larger effects of SLR exposure on municipal bond spreads because bondholder losses in default would be greater in the areas where we see price effects. To quantify this counterfactual, we extend the structural model of credit risk to include bankruptcy costs in Internet Appendix Section A4.2. When bankruptcy costs are higher, as in a Chapter 9 state relative to a proactive state, a reduction in asset values or an

[29]While proactive states provide support, they neither explicitly nor implicitly guarantee local government debt. There are prominent examples of issuers from proactive states defaulting and imposing large losses on bondholders in recent history, including Harrisburg, Pennsylvania in 2009 with an out-of-court restructuring, and Detroit, Michigan in 2013 with the largest Chapter 9 filing to date. State intervention in the case of municipal distress is also distinct from the the situation in California, which is excluded from our sample because Proposition 13 weakens the link between property values and tax revenues.

increase in volatility has a larger impact on credit spreads. However, this is a second-order effect: a 10% increase in bankruptcy cost, analogous to the difference in recoveries between Chapter 9 and proactive states documented by Gao, Lee, and Murphy (2019), leads to a proportional increase of approximately 3% in the effect of fundamental shocks.

In a related vein, the financial health of state governments could affect the likelihood of conditional transfers to exposed school districts. Particularly relevent are the unfunded public pension liabilities that Rauh (2016) estimates are worth \$3.8 trillion. However, 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 price effects when portfolio values collapsed during the financial crisis, as in 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 offset the slight attenuation of the SLR premium from state-level support for distressed municipalities.

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 begins to price SLR exposure in 2013, after which we observe that exposed issuers have significantly higher borrowing costs than unexposed issuers. In 2015, a one standard deviation increase in SLR exposure corresponds to a 5.3 bp increase in credit spreads. We observe significant effects at both short and long maturities, with stronger effects for long-maturity bonds. The lack of similar effects based on measures of short-term flood risk suggests that long-run SLR risk is the primary driver of our results.

In addition to addressing the question of how SLR risk impacts municipal borrowing costs, a contribution of this paper is to adapt a structural model of credit risk from the corporate finance literature to interpret the SLR exposure premium and quantify the economic fundamentals that could explain it. 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.

We find that the increase in expected default losses attributable to SLR risk is low, but that the economic impact is non-trivial, equivalent to a reduction of 2.4% to 5.6% in the present value of local government cash flows or a proportional increase of 1.6% to 2.9% in the volatility of these cash flows. After presenting novel evidence that district-level house prices are unresponsive to SLR exposure and do not affect the estimates of the SLR premium in bonds, we conclude that municipal bond investors are pricing the uncertainty and downside risks associated with SLR's future impact rather than the effects of reduced asset values today. These estimates shed light on the value that could be unlocked by climate remediation efforts in coastal communities.

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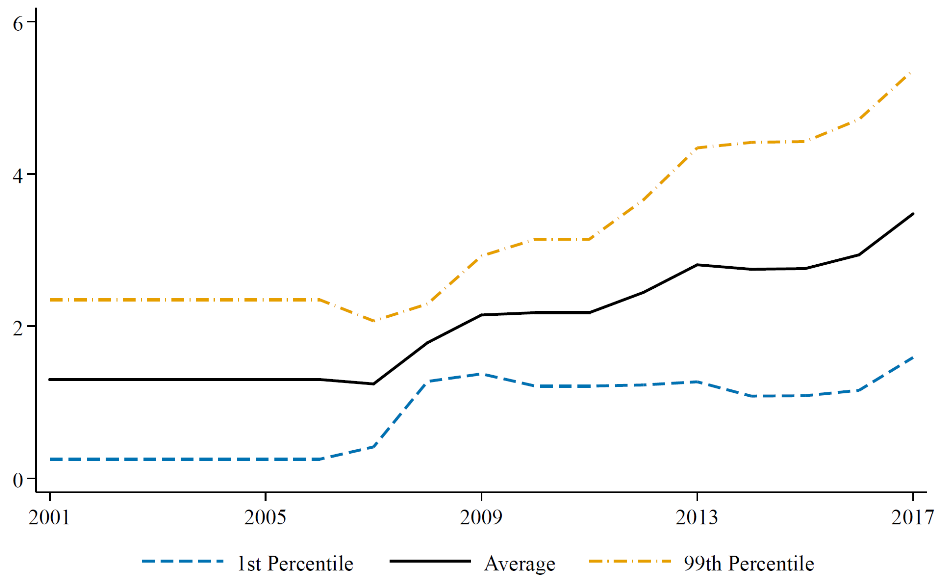
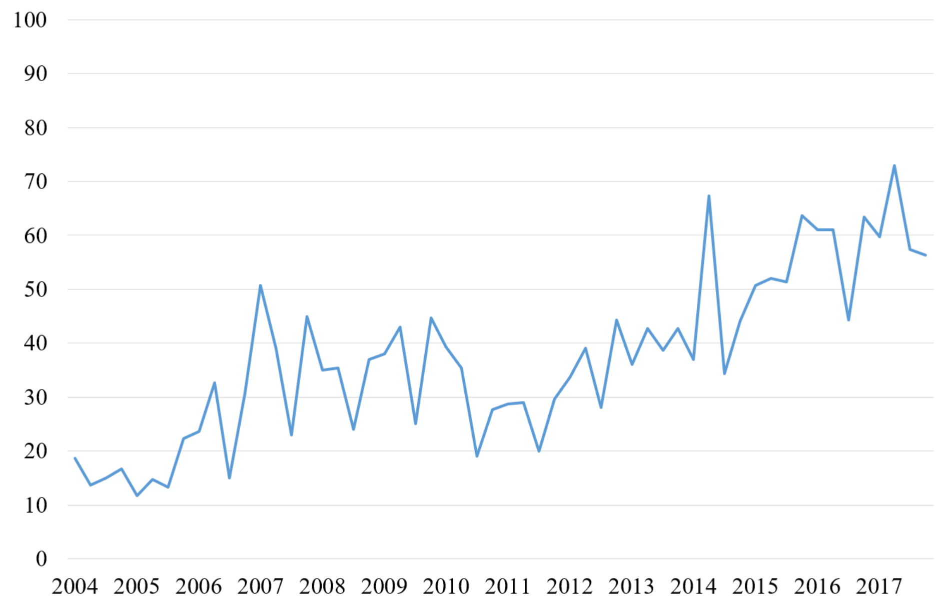
Figure 1: Time Series of Sea Level Rise Projections and Search Trends

Panel A: Scientific Projections of Sea Level Rise

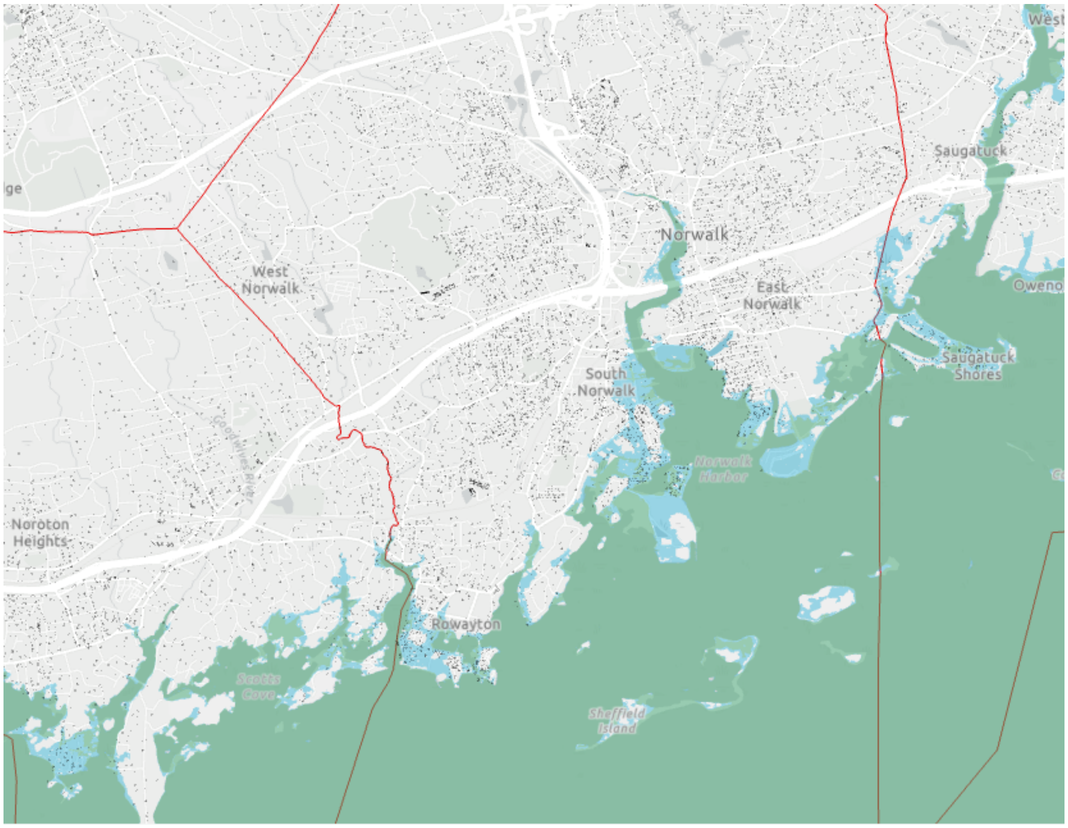


Panel B: Google Search Trends



Note: This figure presents the evolution of sea level rise (SLR) forecasts and popular interest in SLR over our sample period. Panel A reports the distribution 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 Internet Appendix Table A1. 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 normalized to 100. We average the monthly data over each calendar quarter to smooth out high-frequency fluctuations in the series.

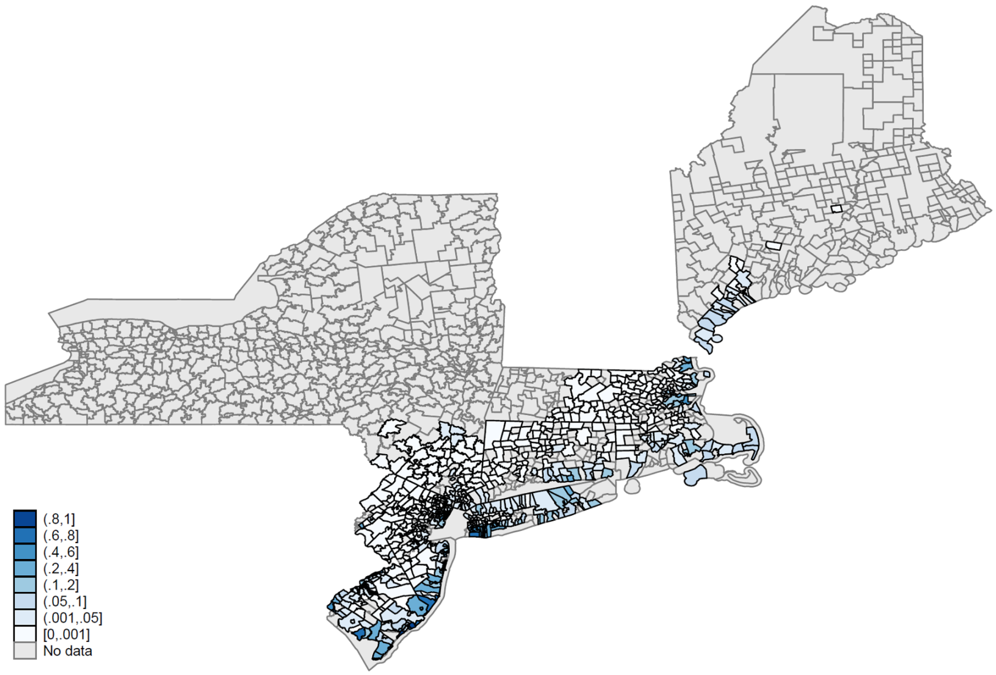
Figure 2: Sea Level Rise Exposure in Fairfield County, Connecticut



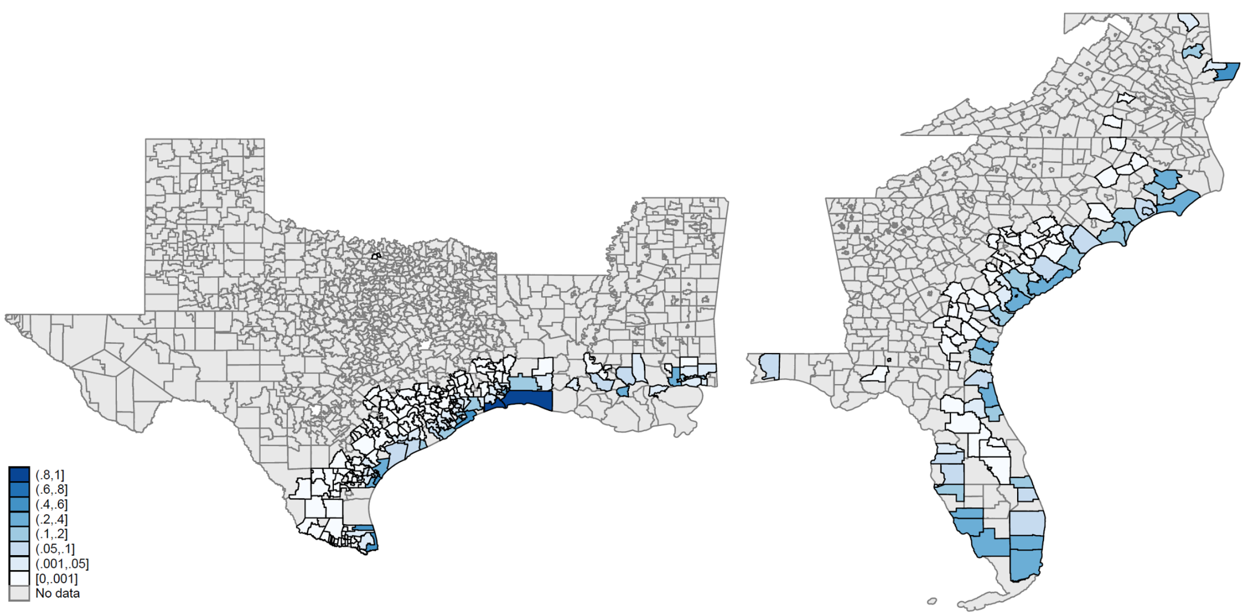
Note: This figure maps housing locations and exposure to sea level rise for a portion of Fairfield County, Connecticut. Black dots are residential dwelling units, the green area is the three-foot NOAA SLR scenario, the light blue area is the six-foot scenario, and the red lines delineate school districts.

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

Panel A: Northeast



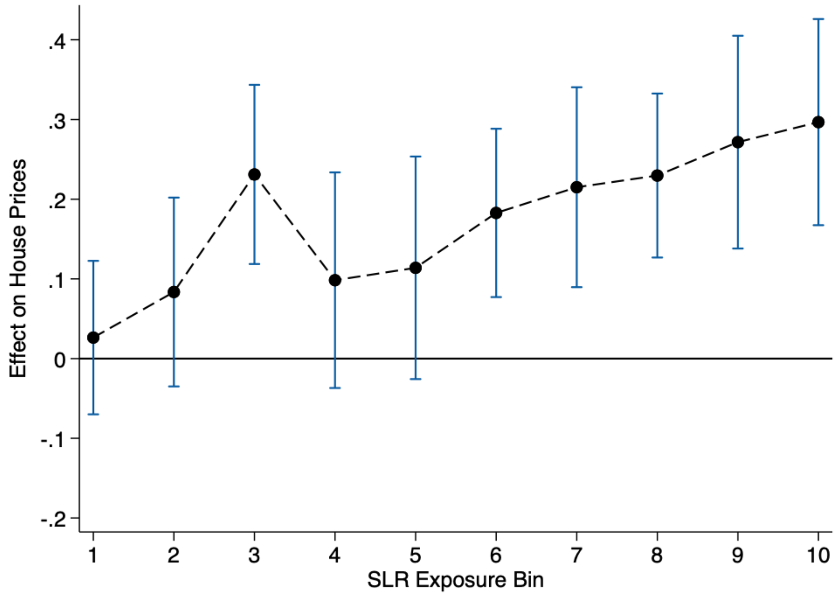
Panel B: Southeast and Gulf Coast



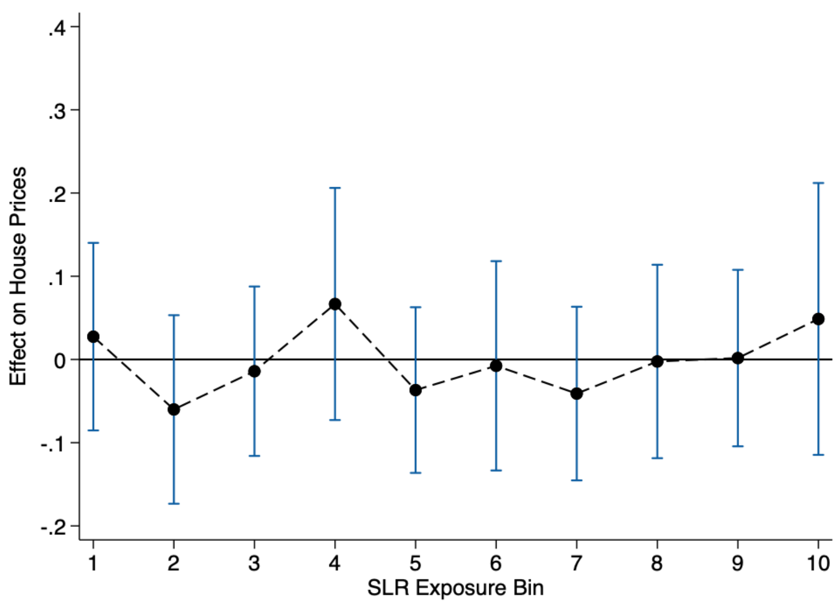
Note: This figure maps the fraction of properties in each coastal school district that is exposed to chronic tidal flooding after six feet of global average sea level rise. Gray areas represent districts that do not appear in the sample of municipal bonds described in Section 2. For ease of presentation,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

Figure 4: Evidence on the Correlation between SLR Risk and Local Economic Conditions

Panel A: State-Year Fixed Effects

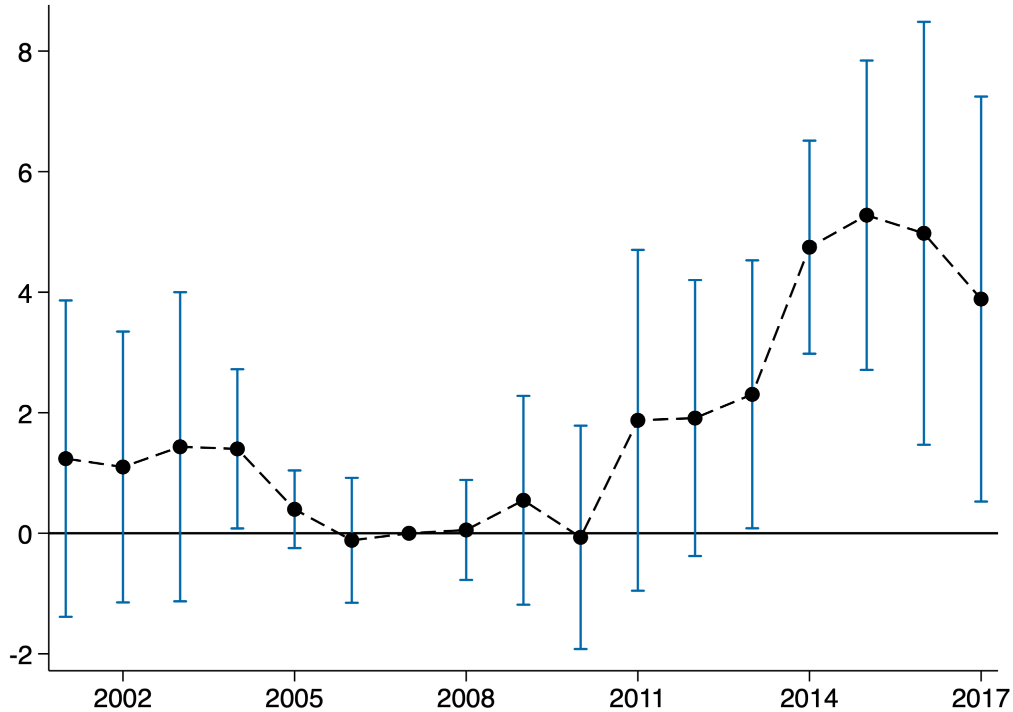


Panel B: County-Year Fixed Effects



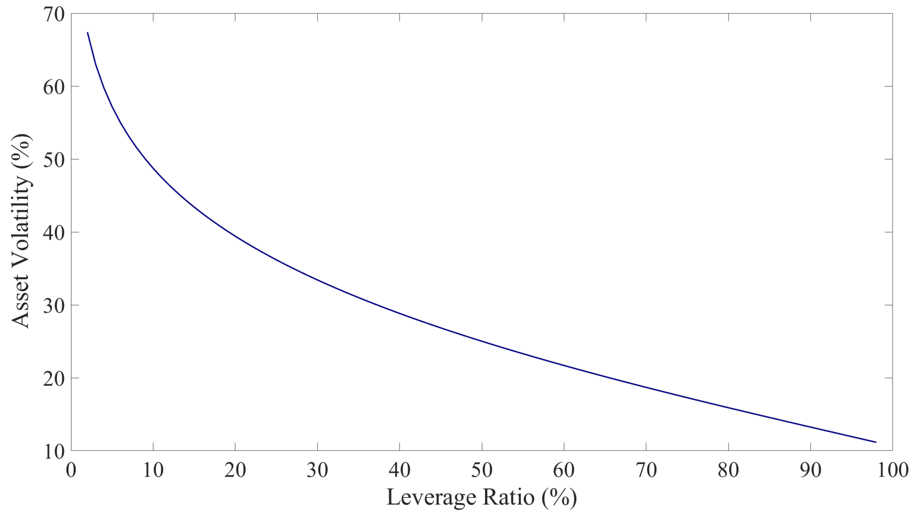
Note: This figures plots coefficients from semi-parametric regressions of log median house prices on SLR exposure. Geographic areas are sorted into decile bins based on the fraction of properties exposed to six feet of SLR. Coefficients on the decile indicators are estimated relative to areas with zero exposure. Panel A measures SLR exposure and annual median house prices at the county level and includes state-year fixed effects. Panel B measures SLR exposure and annual median house prices by school district and includes county-year fixed effects.

Figure 5: Effect of Sea Level Rise Exposure on Bond Credit Spreads



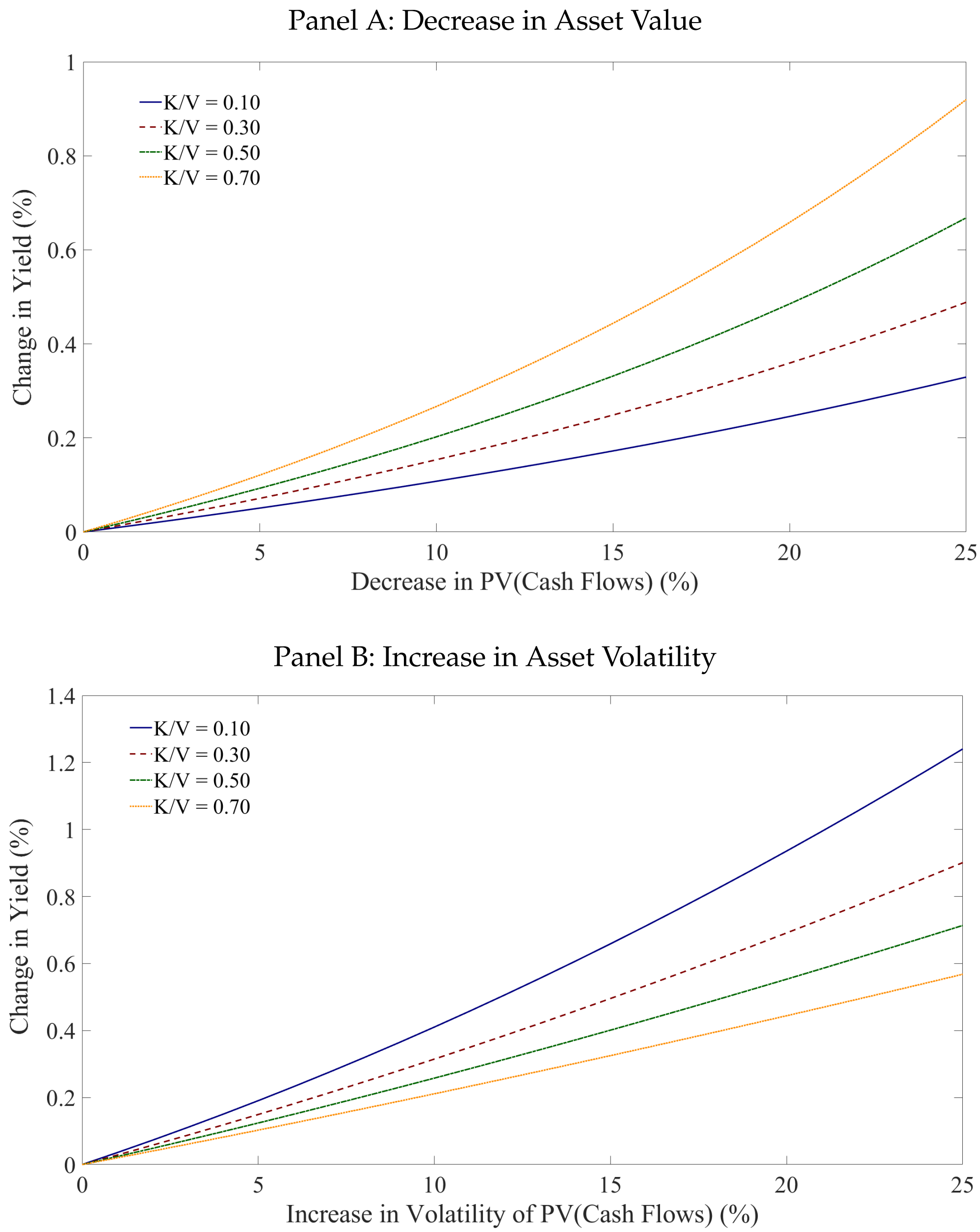
Note: This figure plots the annual effect of SLR exposure on municipal bond credit spreads. Each point is a coefficient from the regression specified in equation (1), while the vertical bars represent 95% confidence bands based on standard errors clustered by county and year-month. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. The regression includes county-year-month and school district fixed effects; the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. The baseline period for the district fixed effects is 2007.

Figure 6: Model-Implied Asset Volatility as a Function of Leverage

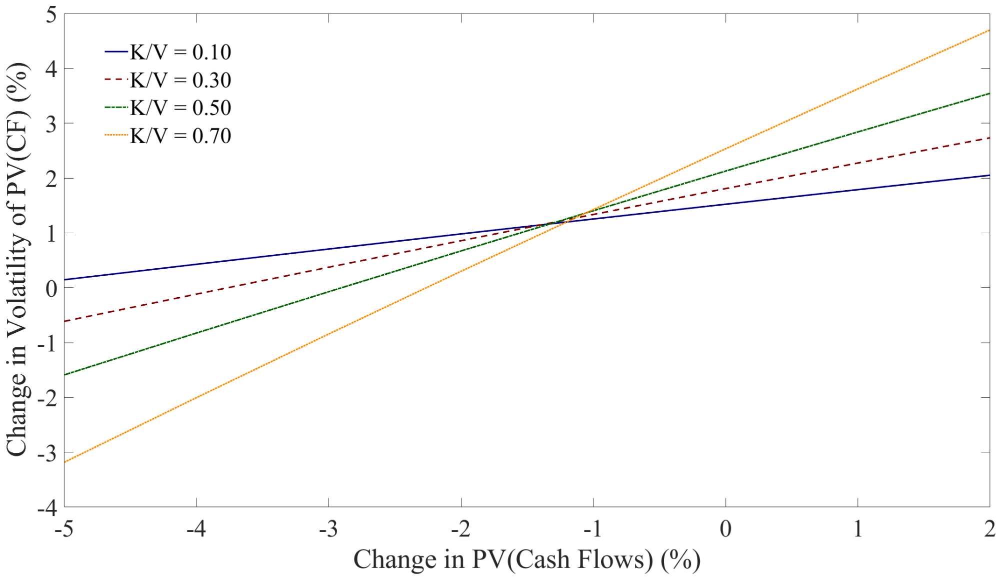


Note: This figure plots the model-implied volatility (σ) from equation (3) as a function of the leverage ratio (K/V). The other model parameters are: $y = 3.24\%$, $r = 2.68\%$, and $T = 7.5$.

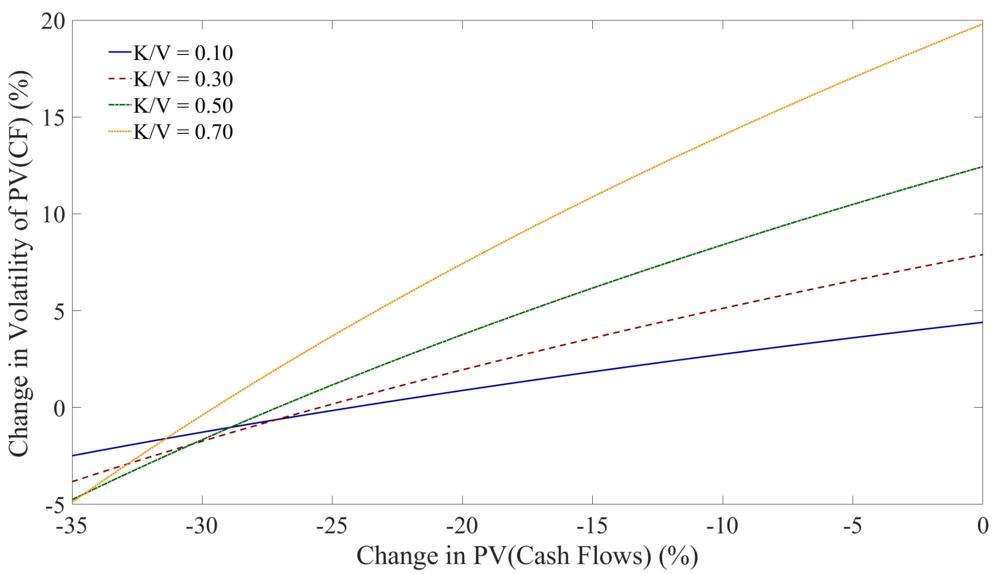
Figure 7: Effects of Asset Value and Volatility Shocks on Municipal Bond Yields



Panel C: Calibration of Shocks to Our Estimates

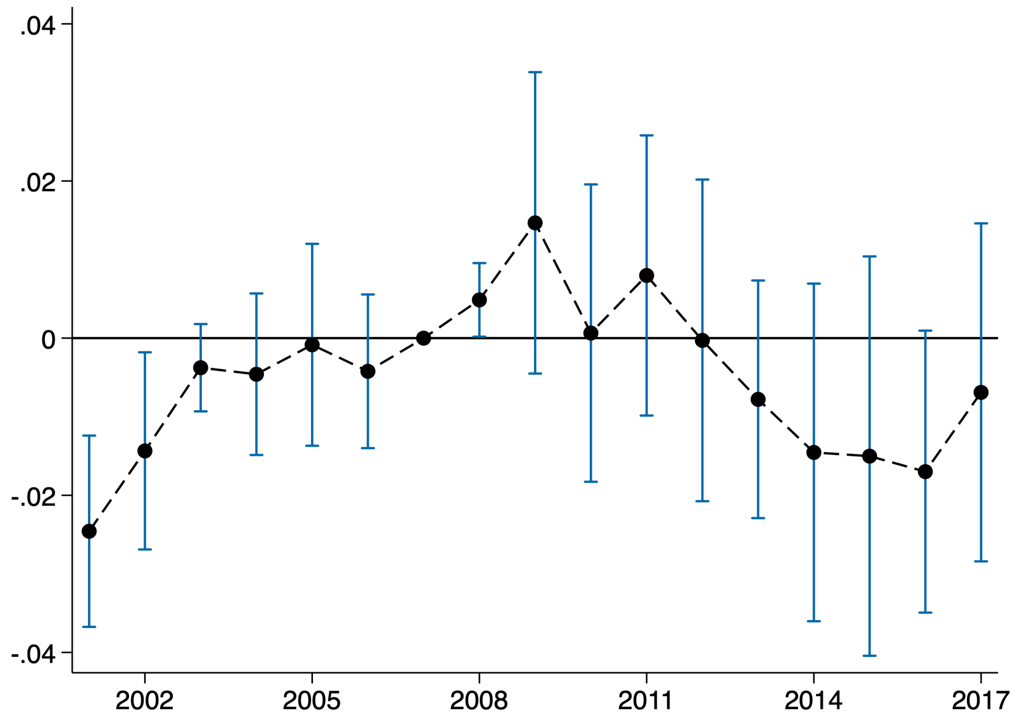


Panel D: Calibration of Shocks to Painter (2020)



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. Panel C considers the combination of asset value and volatility shocks that match our main reduced-form estimate of a 5.3 bp increase in yield. Panel D considers the combination of shocks that matches the 23.4 bp increase in yield estimated by Painter (2020). 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 6. The other model parameters for Panels A, B and C are: $y = 3.24\%$, $r = 2.68\%$, and $T = 7.5$. The parameters for Panel D, which match the typical long-maturity bond in Painter (2020), are: $y = 4.70\%$, $r = 4.00\%$, and $T = 22.5$.

Figure 8: Effect of SLR Exposure on District-Level House Prices



Note: This figure plots the annual effect of SLR exposure on log median house prices at the school-district level. Each point is a coefficient from the regression specified in equation (1), while the vertical bars represent 95% confidence bands based on standard errors clustered by county and year-month. Log(Median House Price) is the annual median transaction price for single-family residences in the school district. District-year observations must have at least 50 transactions to be included in the sample. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. The regression includes county-year-month and school district fixed effects; controls for bond characteristics including the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues.The baseline period for the district fixed effects is 2007.

Table 1: Summary Statistics

	(1) *Full Coastal Sample*			(2) *SLR Exposed Districts*		
	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.
Fraction of Properties Exposed (6 foot SLR)	0.03	0.09	175,415	0.07	0.13	80,406
Storm Surge Exposure	0.61	1.47	175,415	1.26	1.93	80,406
Yield-to-Maturity (%)	3.24	1.24	175,415	3.23	1.21	80,406
MMA AAA-Rated Tax-Exempt Rate (%)	2.68	1.29	175,415	2.65	1.27	80,406
Spread over MMA Curve (bps)	56.54	54.34	175,415	58.07	55.32	80,406
Time to Maturity	9.54	6.12	175,415	9.26	5.86	80,406
Bond Age	4.02	2.70	175,415	3.95	2.67	80,406
Monthly Trading Volume ($000s)	543.03	2797.48	175,415	529.05	2783.86	80,406
Monthly Turnover	0.18	0.37	174,893	0.18	0.37	80,126
Monthly S.D. of Price (per $100)	0.88	0.69	155,689	0.89	0.69	71,115
1(Callable)	0.61	0.49	175,415	0.61	0.49	80,406
1(Insured)	0.41	0.49	175,415	0.46	0.50	80,406
1(General Obligation)	1.00	0.07	175,415	0.99	0.07	80,406
Residents' Average Income ($000s)	37.92	25.05	175,415	36.36	23.18	80,406
Property Tax Rate	0.02	0.00	175,415	0.02	0.00	80,406
School Local Funding	0.51	0.03	175,415	0.51	0.03	80,406
State Worry	55.42	4.30	175,415	55.88	4.53	80,406

Note: This table reports the summary statistics for the variables used in our regression analysis. Observations are at the bond-year-month level. SLR Exposed Districts are school districts with non-zero exposure to six feet of sea level rise. Fraction of Properties Exposed and Storm Surge Exposure are equal to the number of properties exposed to six feet of global SLR and the storm surge associated with a Category 3 hurricane, respectively, divided by the total number of properties in a school district. Yield-to-Maturity is the discount rate that equates the volume-weighted average price in the bond-year-month to the present value of its promised cash flows. MMA AAA-Rated Tax-Exempt Rate is the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, available on Bloomberg. Spread over MMA Curve is the difference between yield-to-maturity and the tax-exempt benchmark rate. Time to Maturity is the number of years between the last transaction date in the bond-year-month and the bond's maturity date. Bond Age is the number of years between the bond's offering date and the last transaction date in the bond-year-month. Monthly Trading Volume is the par value traded in the bond-year-month. Monthly Turnover is the ratio of trading volume to the bond's principal amount. Month S.D. of Price is the standard deviation of transaction prices in the bond-year-month. 1(Callable), 1(Insured), and 1(General Obligation) are indicators for callable, insured, and general obligation bonds, respectively. Residents' Average Income is the average income by district-year using data from the Internal Revenue Service (IRS) Statistics of Income program. Property Tax Rate is the effective property tax rate at the state-year level from the Tax Foundation. School Local Funding is the fraction of school funding drawn from within the school district at the state-year level. State Worry is a state-level measure of global warming concerns from the Yale Climate Opinion Map (Howe et al. (2015)).

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

	(1)	(2)	(3)
SLR Exposure	-1.275**		
	(-2.05)		
SLR Exposure × 1(Year 2001)	0.061	0.313	1.238
	(0.05)	(0.36)	(0.92)
SLR Exposure × 1(Year 2002)	0.475	0.455	1.100
	(0.48)	(0.62)	(0.96)
SLR Exposure × 1(Year 2003)	-0.146	-0.203	1.435
	(-0.19)	(-0.22)	(1.10)
SLR Exposure × 1(Year 2004)	-2.343**	-2.018*	1.400**
	(-2.60)	(-1.77)	(2.08)
SLR Exposure × 1(Year 2005)	-0.655	-0.386	0.398
	(-1.24)	(-0.70)	(1.21)
SLR Exposure × 1(Year 2006)	-0.245	-0.424	-0.117
	(-0.38)	(-0.73)	(-0.22)
SLR Exposure × 1(Year 2008)	0.868	0.610	0.055
	(1.02)	(0.84)	(0.13)
SLR Exposure × 1(Year 2009)	1.911**	1.277*	0.548
	(2.26)	(1.93)	(0.62)
SLR Exposure × 1(Year 2010)	0.915	0.041	-0.068
	(0.69)	(0.03)	(-0.07)
SLR Exposure × 1(Year 2011)	2.357*	1.332	1.875
	(1.89)	(1.20)	(1.30)
SLR Exposure × 1(Year 2012)	1.956	0.930	1.911
	(0.94)	(0.43)	(1.64)
SLR Exposure × 1(Year 2013)	2.964	1.844	2.305**
	(1.34)	(0.80)	(2.03)
SLR Exposure × 1(Year 2014)	5.839*	4.852	4.747***
	(1.90)	(1.41)	(5.26)
SLR Exposure × 1(Year 2015)	5.310*	4.618	5.277***
	(1.84)	(1.40)	(4.03)
SLR Exposure × 1(Year 2016)	5.234*	4.770*	4.977***
	(2.00)	(1.76)	(2.78)
SLR Exposure × 1(Year 2017)	5.336**	4.973**	3.886**
	(2.29)	(2.23)	(2.27)
Controls	N	N	Y
District FE	N	Y	Y
County-Year-Month FE	Y	Y	Y
Outcome Mean	56.541	56.541	57.399
Outcome SD	54.304	54.304	54.594
Observations	175,415	175,415	155,212

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, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. The baseline period for the district fixed effects is 2007.*t*-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote *p*-values less than 0.10, 0.05, and 0.01, respectively.

Table 3: Effect of SLR Exposure on Bond Spreads by Maturity

	(1)	(2)	(3)
SLR Exposure × 1(Post)	2.940**	2.757**	
	(2.18)	(2.40)	
SLR Exposure × 1(Post) × Log(Maturity)			1.270**
			(2.36)
Maturity Range	> 10 years	< 10 years	All
Controls	Y	Y	Y
District FE	Y	Y	N
County-Year-Month FE	Y	Y	N
District-Year-Month FE	N	N	Y
Outcome Mean	58.679	56.528	57.598
Outcome SD	48.883	58.436	54.470
Observations	65,193	90,019	155,212

Note: This table reports estimates of equation (1) with the yearly coefficients collapsed into pre-2013 and post-2012 periods. Observations are at the bond-year-month level. Columns (1) and (2) restrict the sample to bonds with greater than and less than 10 years to maturity, respectively. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table 4: Effect of SLR Exposure versus Storm Surge Exposure

	(1)	(2)	(3)
SLR Exposure × 1(Post)	3.667**	7.024***	1.559
	(2.06)	(3.36)	(0.94)
Storm Surge Exposure × 1(Post)	-0.507	-5.730	1.799
	(-0.21)	(-1.62)	(0.72)
Maturity Range	All	> 10 years	< 10 years
Controls	Y	Y	Y
District FE	Y	Y	Y
County-Year-Month FE	Y	Y	Y
District-Year-Month FE	N	N	N
Outcome Mean	57.399	58.679	56.528
Outcome SD	54.594	48.883	58.436
Observations	155,212	65,193	90,019

Note: This table reports estimates of equation (1), with the yearly coefficients collapsed into pre-2013 and post-2012 periods, and an added interaction between the post-2012 indicator and our measure of storm surge exposure. Observations are at the bond-year-month level. Columns (2) and (3) restrict the sample to bonds with greater than and less than 10 years to maturity, respectively. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. Storm Surge Exposure is the average number of feet of inundation for residential properties due to the storm surge from a Category 3 hurricane, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. *t*-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote *p*-values less than 0.10, 0.05, and 0.01, respectively.

Table 5: Effect of SLR Exposure on Bond Spreads Controlling for House Prices

	(1)	(2)	(3)	(4)	(5)
SLR Exposure × 1(Post)	4.181***	4.007***	4.143***	4.014***	3.938***
	(5.09)	(4.73)	(4.77)	(5.49)	(4.40)
Log(Median House Price)		-12.362***			-13.722**
		(-2.71)			(-2.27)
Log(MHP Exposed)			0.072		
			(0.54)		
Log(MHP Not Exposed)			-12.049***		
			(-2.97)		
Log(Median Zillow House Price)				-11.019	
				(-0.58)	
Log(House Price 10th Percentile)					-0.509
					(-0.12)
Log(House Price 25th Percentile)					-5.273
					(-0.75)
Log(House Price 75th Percentile)					3.176
					(1.36)
Log(House Price 90th Percentile)					4.565
					(1.50)
Controls	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y	Y
Outcome Mean	57.334	57.334	57.334	57.334	57.335
Outcome SD	55.285	55.285	55.285	55.285	55.287
Observations	127,208	127,208	127,208	127,208	127,197

Note: This table reports estimates of equation (1), with the yearly coefficients collapsed into pre-2013 and post-2012 periods, with various additional controls for district-level house prices. Observations are at the bond-year-month level. Each district-year must have at least 50 annual house transactions recorded in ZTRAXX to be included in the sample. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. Log(Median House Price) is the logarithm of the annual realized median transaction price for single-family residences in the school district. The additional percentiles in Column 4 reflect other parts of the price distribution for single-family residences in that school district-year from the same data source. Log(MHP) Exposed and Unexposed are the logarithms of the annual median transaction prices for properties with zero and nonzero exposure to SLR, respectively. Log(Median Zillow House Price) is the logarithm of the average of the median zip code house price index by Zillow in a district-year (Zillow Home Value Index available here: https://www.zillow.com/research/data/). Log(HP nth Percentile) is the logarithm of the nth percentile of realized transaction prices in a district-year. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues.t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table 6: Effect of SLR Exposure Based on Time Variation in Level and Range of Forecasts

	(1)	(2)	(3)	(4)
SLR Range Exposure	20.550***		10.283***	
	(3.91)		(3.37)	
SLR Median Exposure	-56.121**		-25.999**	
	(-2.62)		(-2.16)	
SLR Range Projection × SLR Exposure		1.037***		0.945***
		(3.45)		(3.44)
SLR Median Projection × SLR Exposure		-0.310		-0.412
		(-0.90)		(-1.02)
Articles for Projection	All	All	Select	Select
Controls	Y	Y	Y	Y
District FE	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y
Outcome Mean	57.399	57.399	57.399	57.399
Outcome SD	54.594	54.594	54.594	54.594
Observations	155,212	155,212	155,212	155,212

Note: This table reports estimates of equation (1), substituting time-series measures of SLR projections for the year indicators in Table 2. In columns (1) and (2) the projections are based on all of the scientific studies surveyed in Garner et al. (2018). Internet Appendix Table A1 lists the select studies used in columns (3) and (4).Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points.SLR Exposure Range is the difference between the fractions of properties in a school district that would be inundated in 2100 under the upper- and lower-bound projections.SLR Exposure Median is the fraction of properties in a district that would be inundated in 2100 under the median projection. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. Forecast Range and Forecast Median are the annual range and median of SLR projections, in feet, from the scientific literature. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. *t*-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote *p*-values less than 0.10, 0.05, and 0.01, respectively.

Table 7: Effect of SLR Exposure on Bond Spreads by Local Beliefs

	(1)	(2)	(3)
SLR Exposure $\times$ 1(Post)	4.811***	-0.972	3.968***
	(5.97)	(-0.53)	(4.19)
SLR Exposure $\times$ 1(Post) $\times$ State Worry			2.938**
			(2.62)
Level of Concern	Worried	Not Worried	All
Controls	Y	Y	Y
District FE	Y	Y	Y
County-Year-Month FE	Y	Y	Y
Outcome Mean	53.480	61.035	57.399
Outcome SD	53.830	55.045	54.594
Observations	74,869	80,343	155,212

Note: This table reports estimates of equation (1) with the yearly coefficients collapsed into pre-2013 and post-2012 periods, and an added interaction with state residents' level of concern about global warming. Observations are at the bond-year-month level. Worried states in Column (1) include (in order of concern) New York, Massachusetts, New Jersey, Rhode Island, Connecticut, and Maine, while Not Worried states in Column (2) include Texas, North Carolina, South Carolina, Mississippi, and Louisiana. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. State Worry is a measure of global warming concerns from the Yale Climate Opinion Map, normalized to zero mean and unit standard deviation. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues.*t*-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote *p*-values less than 0.10, 0.05, and 0.01, respectively.

Table 8: Effect of SLR Exposure on Bond Spreads by Tax Regime

	(1)	(2)	(3)
SLR Exposure $\times$ 1(Post)	2.056*	-2.608	-0.763
	(1.67)	(-0.99)	(-1.06)
SLR Exposure $\times$ 1(Post) $\times$ Property Tax Rate	1.148**		
	(2.35)		
SLR Exposure $\times$ 1(Post) $\times$ School Local Funding		6.161**	
		(2.49)	
Sample	Main	Main	CA
Controls	Y	Y	Y
District FE	Y	Y	Y
County-Year-Month FE	Y	Y	Y
Outcome Mean	57.399	57.399	70.214
Outcome SD	54.594	54.594	63.413
Observations	155,212	155,212	128,626

Note: This table reports estimates of equation (1), with the yearly coefficients collapsed into pre-2013 and post-2012 periods, and an added interaction with measures of school districts' reliance on property taxes. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. Property Tax Rate is the effective property tax rate at the state level, normalized to zero mean and unit standard deviation. School Local Funding is the fraction of school funding drawn from within the school district, normalized to zero mean and unit standard deviation. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table 9: Effect of SLR Exposure on Bond Spreads by State Distress Policy

	(1)	(2)	(3)	(4)
SLR Exposure × 1(Post)	4.921***	-0.968	-13.767***	-2.015
	(6.05)	(-0.52)	(-3.12)	(-1.48)
SLR Exposure × 1(Post) × 1(Proactive)				6.893***
				(4.47)
Distress Policy	Proactive	Chapter 9	Neither	All
Controls	Y	Y	Y	Y
District FE	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y
Outcome Mean	53.284	61.063	59.146	57.399
Outcome SD	53.460	55.196	57.155	54.594
Observations	71,711	78,283	5,218	155,212

Note: This table reports estimates of equation (1), with the yearly coefficients collapsed into pre-2013 and post-2012 periods, and an added interaction with indicators for state-level policies regarding municipal distress. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. State distress policies are coded according to Gao, Lee, and Murphy (2019): Proactive states include Maine, New Jersey, New York, and North Carolina; Chapter 9 states include South Carolina and Texas; and Neither states include Connecticut, Louisiana, Massachusetts, Mississippi, and Rhode Island. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. *t*-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote *p*-values less than 0.10, 0.05, and 0.01, respectively.

Sea Level Rise Exposure and Municipal Bond Yields
Internet Appendix

This appendix provides supplementary analysis for "Sea Level Rise Exposure and Municipal Bond Yields." It describes the sample of scientific studies on sea level rise (SLR) and the construction of a relative sea level rise (RSLR) measure, provides evidence on the robustness of our main regression estimates, extends the structural model of credit risk on several dimensions, and replicates the results in Painter (2020) on a year-by-year basis.

Contents

A1 Selection of Sea Level Rise Studies

This section describes the process by which we construct the panel dataset used to measure the variation in global sea level rise projections for the year 2100 over our sample period.

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. We construct one set of measures based on this full set of studies and denote this sample "All" articles.

We also construct our projection measures using a filtered sample, which we denote the "select" articles. Most studies model their SLR projections based on agreed-upon emissions scenarios, which change in 2012 with the release of Representative Carbon Pathways (RCP). 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 in our select sample, listed in Appendix Table A1.

Table A1: List of Sea Level Rise Studies

			Mid Scenario			High Scenario			
Author	Type	Year	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).

A2 Measurement of Relative Sea Level Rise

As discussed in Section 2 of the paper, Murfin and Spiegel (2020) argue that the main SLR exposure measure does not account for subsidence, so it 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" (`https://coast.noaa.gov/data/digitalcoast/pdf/slr-faq.pdf`). In other words, the NOAA measure is based on more predictable and better understood factors, but may miss some less predictable aspects of SLR exposure.

The relative sea level rise (RSLR) measure proposed by Murfin and Spiegel (2020) could capture missing factors and represent SLR risk more accurately. Alternatively, it could introduce noise, as suggested by the NOAA, and may not represent investors' information sets because it is not easily accessible through public means. To address this issue, we construct a measure of RSLR exposure to compare results.

Our measure of RSLR exposure is based on Sweet et al. (2017), who forecast regional SLR by extrapolating the observed historical subsidence at tidal monitor stations into the future. They do so for several time periods, including an end-of-century estimate.

We begin by locating the nearest station reported in Sweet et al. (2017) for each residential property in our sample. We then calculate the RSLR adjustment as the difference between the end-of-century global mean sea level (GMSL) under the extreme (2.5 meter) scenario and the local scenario that incorporates the median predicted regional variation. Finally, we obtain the property-level RSLR exposure by subtracting the RSLR adjustment from the NOAA SLR exposure level.

At the house level, indicators for six-foot inundation based on SLR and RSLR have a correlation coefficient of 0.77 – a high degree of correlation, but with meaningful independent variation. However, when we aggregate these measures to the district level, taking the fraction of inundated homes, the correlation between the two measures is 0.97. This strong degree of correlation is because most of the within-district variation is averaged out, resulting in similar variation across districts.

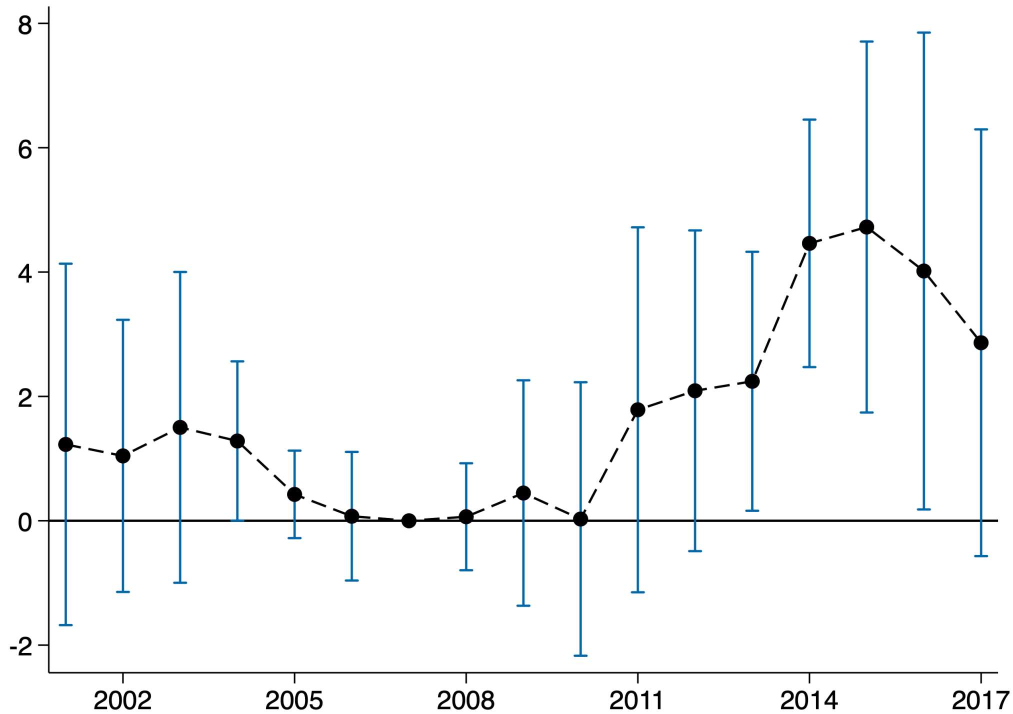
In Table A2 and Figure A1 below, we estimate our main regression specification using both the SLR and RSLR measures and obtain very similar results. The coefficients on the RSLR measure are slightly smaller relative to our SLR measure, but the differences are not statistically significant. The reduced coefficient estimates suggest that the RSLR measure potentially introduces measurement error and attenuation bias.

Table A2: Effects of SLR and RSLR Exposure on Bond Spreads

	(1)	(2)	(3)	(4)
SLR Exposure × 1(Post)	3.340***	2.798**		
	(3.01)	(2.08)		
SLR Exposure × 1(Year 2001)			1.238	1.228
			(0.92)	(0.83)
SLR Exposure × 1(Year 2002)			1.100	1.043
			(0.96)	(0.93)
SLR Exposure × 1(Year 2003)			1.435	1.502
			(1.10)	(1.18)
SLR Exposure × 1(Year 2004)			1.400**	1.283*
			(2.08)	(1.96)
SLR Exposure × 1(Year 2005)			0.398	0.424
			(1.21)	(1.18)
SLR Exposure × 1(Year 2006)			-0.117	0.073
			(-0.22)	(0.14)
SLR Exposure × 1(Year 2008)			0.055	0.065
			(0.13)	(0.15)
SLR Exposure × 1(Year 2009)			0.548	0.446
			(0.62)	(0.48)
SLR Exposure × 1(Year 2010)			-0.068	0.028
			(-0.07)	(0.03)
SLR Exposure × 1(Year 2011)			1.875	1.785
			(1.30)	(1.19)
SLR Exposure × 1(Year 2012)			1.911	2.090
			(1.64)	(1.59)
SLR Exposure × 1(Year 2013)			2.305**	2.243**
			(2.03)	(2.11)
SLR Exposure × 1(Year 2014)			4.747***	4.462***
			(5.26)	(4.39)
SLR Exposure × 1(Year 2015)			5.277***	4.724***
			(4.03)	(3.10)
SLR Exposure × 1(Year 2016)			4.977***	4.017**
			(2.78)	(2.05)
SLR Exposure × 1(Year 2017)			3.886**	2.863
			(2.27)	(1.64)
SLR Measure	SLR	RSLR	SLR	RSLR
Controls	Y	Y	Y	Y
District FE	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y
Outcome Mean	57.399	57.399	57.399	57.399
Outcome SD	54.594	54.594	54.594	54.594
Observations	155,212	155,212	155,212	155,212

Note: This table reports estimates of Table 2 using measures of SLR and relative sea level rise (RSLR) exposure. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure in Column 1 and 3 is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. SLR Exposure in Column 2 and 4 is the fraction of residential properties that would be inundated by six feet of sea level rise, adjusting for local differences in land subsidence and land rebound, as in Murfin and Spiegel (2020). 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. Log(Median House Price) is the annual median transaction price for single-family residences in the school district. The additional percentiles reflect other parts of the price distribution in that school district-year. Log(MHP) Exposed and Unexposed are the annual median transaction prices for single-family residences in the school district for properties with zero and nonzero exposure to SLR, respectively. Zillow House Price Index is a district-year index estimated by averaging the Zillow House Price Measure across zip codes. See Table 5 for additional details on controls. The baseline period for the district fixed effects is 2007. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Figure A1: Effect of RSLR Exposure on Bond Spreads



Note: This figure plots the annual effect of relative sea level rise (RSLR) exposure on municipal bond credit spreads, using the same specification as in Figure 5. Each point is a yearly coefficient from the regression specified in equation (1), while the vertical bars represent 95% confidence bands based on standard errors clustered by county and year-month. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, adjusting for local differences in land subsidence and rebound as in Murfin and Spiegel (2020), and normalized to zero mean and unit standard deviation. The regression includes county-year-month and school district fixed effects; the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. The baseline period for the district fixed effects is 2007.

A3 Supplementary Evidence on the Main Sample

Table A3: Effect of SLR Exposure on Bond Spreads – Including the Initial Months of Trading

	(1)	(2)	(3)
SLR Exposure	-0.826*		
	(-1.76)		
SLR Exposure × 1(Year 2001)	-0.317	-0.320	1.158
	(-0.54)	(-0.52)	(1.23)
SLR Exposure × 1(Year 2002)	-0.021	-0.013	0.227
	(-0.02)	(-0.02)	(0.28)
SLR Exposure × 1(Year 2003)	-2.007*	-1.543	0.771
	(-1.68)	(-1.08)	(0.77)
SLR Exposure × 1(Year 2004)	-1.720***	-1.071	0.851
	(-3.59)	(-1.27)	(1.37)
SLR Exposure × 1(Year 2005)	-0.634	-0.552	0.130
	(-1.12)	(-1.03)	(0.42)
SLR Exposure × 1(Year 2006)	-0.228	-0.372	-0.190
	(-0.43)	(-0.64)	(-0.34)
SLR Exposure × 1(Year 2008)	0.638	0.301	0.300
	(0.89)	(0.46)	(0.66)
SLR Exposure × 1(Year 2009)	0.053	-0.500	-0.065
	(0.05)	(-0.54)	(-0.08)
SLR Exposure × 1(Year 2010)	1.176	0.288	-0.329
	(1.06)	(0.24)	(-0.40)
SLR Exposure × 1(Year 2011)	2.291**	1.332	2.048*
	(2.28)	(1.17)	(1.81)
SLR Exposure × 1(Year 2012)	1.133	0.085	1.525*
	(0.71)	(0.05)	(1.80)
SLR Exposure × 1(Year 2013)	2.540	1.476	2.076***
	(1.34)	(0.68)	(3.21)
SLR Exposure × 1(Year 2014)	3.704	2.926	3.718***
	(1.60)	(1.10)	(3.40)
SLR Exposure × 1(Year 2015)	3.018*	2.466	3.863***
	(1.67)	(1.21)	(3.05)
SLR Exposure × 1(Year 2016)	4.251*	3.892	3.386***
	(1.79)	(1.67)	(2.84)
SLR Exposure × 1(Year 2017)	4.143**	3.829*	3.163**
	(2.10)	(1.97)	(2.30)
Controls	N	N	Y
District FE	N	Y	Y
County-Year-Month FE	Y	Y	Y
Outcome Mean	50.907	50.907	51.665
Outcome SD	52.576	52.576	52.910
Observations	218,021	218,021	192,835

Note: In this table we replicate Table 2 of the paper after dropping the restriction that trades must occur more than three months after the bond is issued. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is defined as the fraction of residential properties that would be inundated by six feet of sea level rise.

Table A4: Effect of SLR Exposure on Bond Spreads – Unbalanced Panel

	(1)	(2)	(3)
SLR Exposure	-0.253		
	(-0.62)		
SLR Exposure × 1(Year 2001)	-0.309	-0.551	-0.048
	(-0.31)	(-0.52)	(-0.05)
SLR Exposure × 1(Year 2002)	-0.235	-0.181	0.444
	(-0.29)	(-0.23)	(0.92)
SLR Exposure × 1(Year 2003)	-0.306	-0.666	0.678
	(-0.38)	(-0.84)	(0.97)
SLR Exposure × 1(Year 2004)	-1.518***	-1.276*	0.399
	(-2.82)	(-1.83)	(0.73)
SLR Exposure × 1(Year 2005)	-0.249	0.095	0.099
	(-0.63)	(0.22)	(0.23)
SLR Exposure × 1(Year 2006)	-0.820**	-0.754**	-0.247
	(-2.01)	(-2.03)	(-0.53)
SLR Exposure × 1(Year 2008)	0.612	0.614	0.026
	(1.25)	(1.31)	(0.12)
SLR Exposure × 1(Year 2009)	-0.020	-0.287	-0.437
	(-0.02)	(-0.40)	(-0.78)
SLR Exposure × 1(Year 2010)	-0.417	-0.396	-0.234
	(-0.53)	(-0.44)	(-0.37)
SLR Exposure × 1(Year 2011)	-0.254	-0.285	0.167
	(-0.26)	(-0.31)	(0.17)
SLR Exposure × 1(Year 2012)	-1.559	-1.437	0.132
	(-1.45)	(-1.14)	(0.11)
SLR Exposure × 1(Year 2013)	1.279	0.996	0.745
	(1.02)	(0.63)	(0.79)
SLR Exposure × 1(Year 2014)	1.940	1.993	1.657
	(1.34)	(1.03)	(1.63)
SLR Exposure × 1(Year 2015)	2.596*	2.799	2.190*
	(1.97)	(1.54)	(1.79)
SLR Exposure × 1(Year 2016)	3.411**	3.738**	2.513**
	(2.44)	(2.38)	(2.01)
SLR Exposure × 1(Year 2017)	4.278***	4.667***	2.338**
	(4.21)	(4.07)	(2.40)
Controls	N	N	Y
District FE	N	Y	Y
County-Year-Month FE	Y	Y	Y
Outcome Mean	55.700	55.700	56.592
Outcome SD	53.138	53.139	53.446
Observations	285,412	285,412	250,882

Note: In this table we replicate Table 2 in the paper after relaxing the "balanced panel" restriction. Specifically, we drop the requirement that each county have more than one district and that each district have at least one secondary market bond price observation per year. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is defined as the fraction of residential properties that would be inundated by six feet of sea level rise.

Table A5: Effect of SLR Exposure on Bond Spreads – Robustness Specifications

	(1)	(2)	(3)
SLR Exposure × 1(Year 2001)	1.903	0.787	2.885*
	(1.37)	(0.70)	(1.82)
SLR Exposure × 1(Year 2002)	2.140	0.850	1.256
	(1.33)	(0.87)	(1.17)
SLR Exposure × 1(Year 2003)	2.391	1.102	1.812
	(1.55)	(1.08)	(1.59)
SLR Exposure × 1(Year 2004)	1.164	1.159	1.387***
	(1.64)	(1.62)	(2.76)
SLR Exposure × 1(Year 2005)	0.093	0.234	0.151
	(0.28)	(0.72)	(0.51)
SLR Exposure × 1(Year 2006)	0.517	-0.169	-0.075
	(0.82)	(-0.39)	(-0.14)
SLR Exposure × 1(Year 2008)	1.058	-0.085	0.055
	(0.92)	(-0.30)	(0.11)
SLR Exposure × 1(Year 2009)	1.611	0.528	0.455
	(1.05)	(0.73)	(0.41)
SLR Exposure × 1(Year 2010)	2.476	-0.188	0.403
	(1.27)	(-0.23)	(0.35)
SLR Exposure × 1(Year 2011)	3.927**	1.302	2.159
	(2.20)	(0.99)	(1.47)
SLR Exposure × 1(Year 2012)	4.315**	1.120	2.467*
	(2.01)	(1.06)	(1.96)
SLR Exposure × 1(Year 2013)	4.437**	1.390	2.657***
	(2.60)	(1.23)	(2.78)
SLR Exposure × 1(Year 2014)	5.263***	4.079***	4.650***
	(5.31)	(5.49)	(4.32)
SLR Exposure × 1(Year 2015)	5.534***	4.529***	5.020***
	(4.42)	(3.50)	(3.00)
SLR Exposure × 1(Year 2016)	5.013***	4.477***	4.900**
	(3.08)	(2.85)	(2.51)
SLR Exposure × 1(Year 2017)	4.158**	3.654**	4.196**
	(2.06)	(2.57)	(2.47)
Exposure Measure	6-foot, Frac.	4-foot, Frac.	6-foot, Value
State Equal-Weighted	Y	N	N
Controls	Y	Y	Y
District FE	Y	Y	Y
County-Year-Month FE	Y	Y	Y
Observations	155,212	155,212	155,212

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, in basis points. SLR Exposure is defined differently across the columns. In column (1) SLR exposure is measured as the fraction of properties exposed to a 6-foot SLR, as is our main analyses in the paper. The difference between column (1) and the analysis in the paper is that column (1) weights each observation by one over the number of observations in the state, thus assigning equal weight to each state in the sample. In column (2) SLR exposure is measured as the fraction of properties exposed to four feet of SLR, while in column (3) it is measured as the percentage of property value that is exposed to six feet of SLR. 2007 is the omitted year for the interaction coefficients. 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 by Maturity – Alternative Post Measures

Panel A: Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)
SLR Exposure × 1(Post) × Log(Maturity)	1.284*	1.214**	1.040***	1.270**	1.034	0.726
	(1.91)	(2.10)	(2.79)	(2.36)	(1.23)	(0.74)
Maturity Range	All	All	All	All	All	All
Post = Year > x	2009	2010	2011	2012	2013	2014
Controls	Y	Y	Y	Y	Y	Y
District FE	N	N	N	N	N	N
County-Year-Month FE	N	N	N	N	N	N
District-Year-Month FE	Y	Y	Y	Y	Y	Y
Outcome Mean	57.598	57.598	57.598	57.598	57.598	57.598
Outcome SD	54	54	54	54	54	54
Observations	155,212	155,212	155,212	155,212	155,212	155,212

Panel B: Long-Maturity Sample

	(1)	(2)	(3)	(4)	(5)	(6)
SLR Exposure × 1(Post)	1.715*	3.172***	3.458***	2.940**	2.539	1.935
	(1.80)	(2.72)	(3.51)	(2.18)	(1.64)	(1.17)
Maturity Range	> 10 years	> 10 years	> 10 years	> 10 years	> 10 years	> 10 years
Post = Year > x	2009	2010	2011	2012	2013	2014
Controls	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y	Y	Y
District-Year-Month FE	N	N	N	N	N	N
Outcome Mean	58.679	58.679	58.679	58.679	58.679	58.679
Outcome SD	49	49	49	49	49	49
Observations	65,193	65,193	65,193	65,193	65,193	65,193

Panel C: Short-Maturity Sample

	(1)	(2)	(3)	(4)	(5)	(6)
SLR Exposure × 1(Post)	1.517**	1.988**	2.097**	2.757**	3.405**	3.147*
	(2.12)	(2.05)	(2.09)	(2.40)	(2.37)	(1.96)
Maturity Range	≤ 10 years	≤ 10 years	≤ 10 years	≤ 10 years	≤ 10 years	≤ 10 years
Post = Year > x	2009	2010	2011	2012	2013	2014
Controls	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y	Y	Y
District-Year-Month FE	N	N	N	N	N	N
Outcome Mean	56.528	56.528	56.528	56.528	56.528	56.528
Outcome SD	58	58	58	58	58	58
Observations	90,019	90,019	90,019	90,019	90,019	90,019

Note: This table reports estimates re-estimating Column 1 from Table 3 using alternative cutoff periods. Each column reflects an alternative cutoff period. Observations are at the bond-year-month level. Panel A reflects all maturities pooled together. Panel B is bonds with maturity greater than 10 years. Panel C is bonds with maturity less than 10 years. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after the indicated year and zero otherwise. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table A7: Effect of SLR Exposure versus Storm Surge Exposure – Alternative Post Measures

	(1)	(2)	(3)	(4)	(5)	(6)
SLR Exposure × 1(Post)	1.751	2.913*	2.811*	3.667**	3.805*	4.283*
	(1.12)	(1.71)	(1.93)	(2.06)	(1.80)	(1.96)
Storm Surge Exposure × 1(Post)	0.845	0.095	0.373	-0.507	-0.063	-1.298
	(0.57)	(0.06)	(0.19)	(-0.21)	(-0.02)	(-0.41)
Maturity Range	All	All	All	All	All	All
Post = Year > x	2009	2010	2011	2012	2013	2014
Controls	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y	Y	Y
District-Year-Month FE	N	N	N	N	N	N
Outcome Mean	57.399	57.399	57.399	57.399	57.399	57.399
Outcome SD	55	55	55	55	55	55
Observations	155,212	155,212	155,212	155,212	155,212	155,212

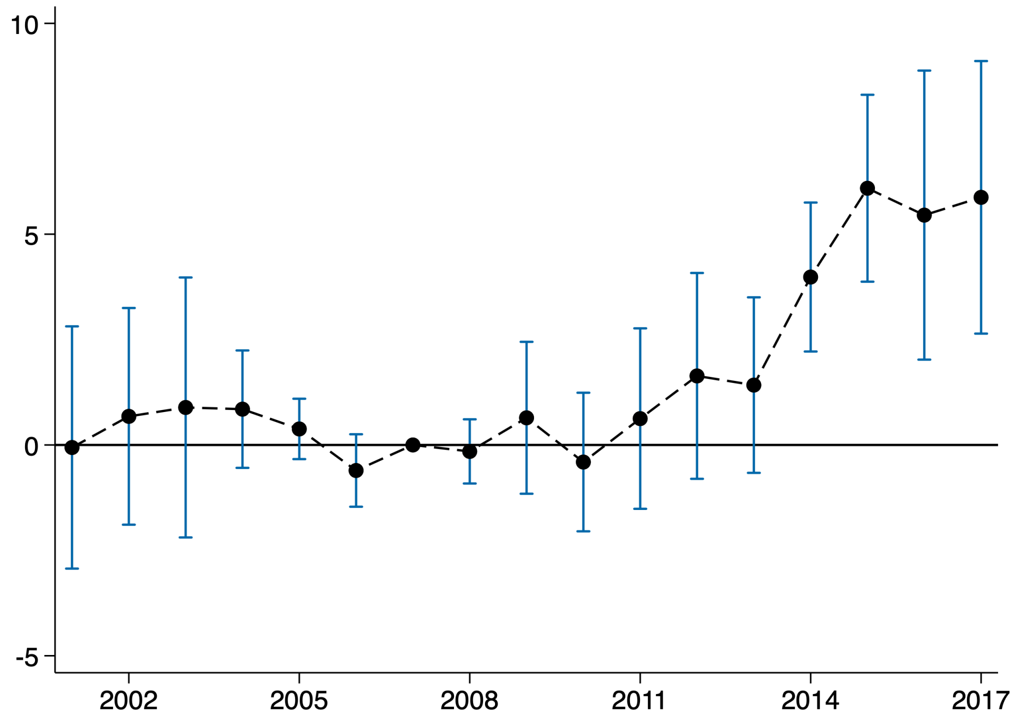
Note: This table reports estimates re-estimating Column 1 from Table 3 using alternative cutoff periods. Each column in this table reflects a different year for the post period. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. Storm Surge Exposure is the fraction of residential properties that would be inundated by six feet of storm surge from a Category 3 hurricane, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after the indicated period and zero otherwise. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. The baseline period for the district fixed effects is 2007. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Table A8: Effect of SLR Exposure on Bond Spreads, Controlling for House Prices

	(1)	(2)	(3)	(4)	(5)
SLR Exposure × 1(Year 2001)	-0.118	-0.422	-0.522	-0.278	-0.060
	(-0.10)	(-0.34)	(-0.44)	(-0.22)	(-0.04)
SLR Exposure × 1(Year 2002)	0.472	0.294	0.298	0.310	0.566
	(0.39)	(0.24)	(0.25)	(0.25)	(0.42)
SLR Exposure × 1(Year 2003)	0.632	0.586	0.559	0.479	0.838
	(0.44)	(0.41)	(0.39)	(0.32)	(0.53)
SLR Exposure × 1(Year 2004)	0.759	0.702	0.732	0.642	0.806
	(1.29)	(1.20)	(1.25)	(0.88)	(1.13)
SLR Exposure × 1(Year 2005)	0.251	0.240	0.294	0.187	0.417
	(0.77)	(0.64)	(0.82)	(0.52)	(1.15)
SLR Exposure × 1(Year 2006)	-0.723	-0.775*	-0.827*	-0.752*	-0.617
	(-1.66)	(-1.84)	(-1.87)	(-1.69)	(-1.45)
SLR Exposure × 1(Year 2008)	-0.330	-0.269	-0.336	-0.298	-0.114
	(-1.35)	(-1.09)	(-1.54)	(-1.11)	(-0.34)
SLR Exposure × 1(Year 2009)	0.214	0.396	0.369	0.254	0.668
	(0.24)	(0.48)	(0.47)	(0.30)	(0.73)
SLR Exposure × 1(Year 2010)	-0.753	-0.745	-0.684	-0.741	-0.393
	(-0.96)	(-1.05)	(-0.98)	(-1.01)	(-0.47)
SLR Exposure × 1(Year 2011)	1.349	1.447	1.422	1.311	0.725
	(0.87)	(0.97)	(0.97)	(0.87)	(0.64)
SLR Exposure × 1(Year 2012)	1.281	1.277	1.368	1.233	1.686
	(1.13)	(1.19)	(1.24)	(1.11)	(1.37)
SLR Exposure × 1(Year 2013)	1.697	1.600	1.620	1.606	1.459
	(1.38)	(1.35)	(1.43)	(1.35)	(1.35)
SLR Exposure × 1(Year 2014)	4.607***	4.427***	4.995***	4.447***	3.994***
	(4.59)	(4.33)	(4.07)	(4.50)	(4.30)
SLR Exposure × 1(Year 2015)	5.908***	5.722***	5.934***	5.715***	6.086***
	(5.38)	(4.82)	(4.91)	(5.52)	(5.37)
SLR Exposure × 1(Year 2016)	5.563***	5.353***	5.216***	5.367***	5.633***
	(3.61)	(3.51)	(3.70)	(3.79)	(3.47)
SLR Exposure × 1(Year 2017)	5.712***	5.627***	5.611***	5.518***	5.930***
	(3.82)	(3.84)	(3.96)	(3.92)	(3.63)
House Price	None	Median HP	Unexp. + Exposed HP	Zillow HP	Full Dist.
Controls	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y	Y
Outcome Mean	57.334	57.334	57.334	57.334	57.335
Outcome SD	55.285	55.285	55.285	55.285	55.287
Observations	127,208	127,208	127,208	127,208	127,197

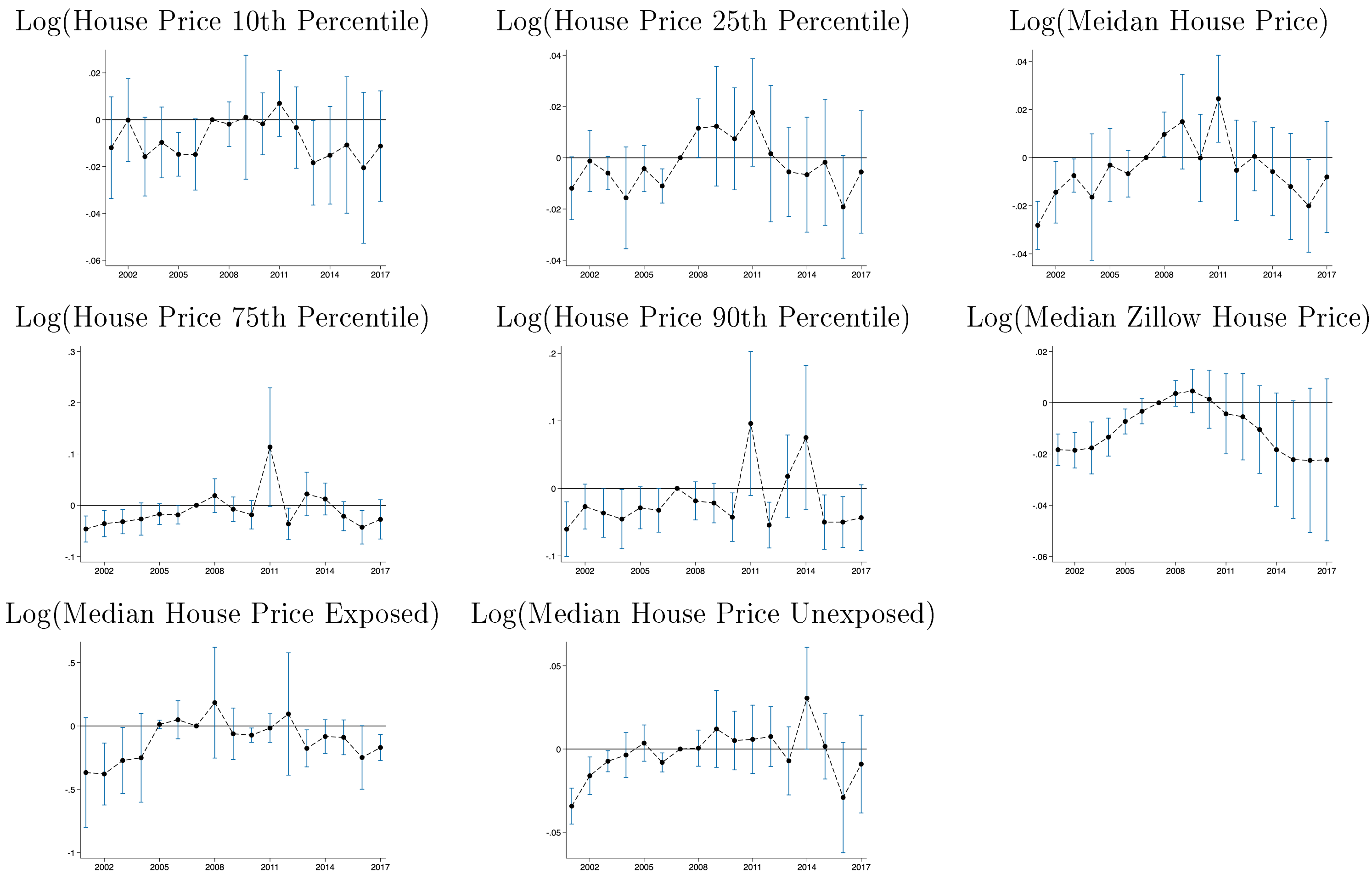
Note: This table reports estimates of Table 5 with the yearly coefficients and various controls for district-level house prices. Observations are at the bond-year-month level. Each district-year must have at least 50 annual house transactions recorded in ZTRAXX to be included in the sample. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. Median HP is the annual median transaction price for single-family residences in the school district. Exposed and Unexposed HP are the annual median transaction prices for single-family residences in the school district for properties with zero and nonzero exposure to SLR, respectively. Zillow House Price Index is a district-year index estimated by averaging the Zillow House Price Measure across zip codes. Full Dist controls for the full transaction price distribution for single-family residences in that school district-year. See Table 5 for additional details on controls. The baseline period for the district fixed effects is 2007. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Figure A2: Effect of SLR Exposure on Bond Credit Spreads, Controlling for House Prices



Note: This figure plots the annual effect of SLR exposure on municipal bond credit spreads, repeating the house price controls from Column 4 of Table 5. Each point is a yearly coefficient from the regression specified in equation (1), while the vertical bars represent 95% confidence bands based on standard errors clustered by county and year-month. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. The regression includes county-year-month and school district fixed effects; the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. The baseline period for the district fixed effects is 2007.

Figure A3: Effect of SLR Exposure on Additional House Price Measures



Note: This figure plots the annual effect of SLR exposure on different house prices measures at the school district level. Each point is a coefficient from the regression specified in equation (1), while the vertical bars represent 95% confidence bands based on standard errors clustered by county and year-month. District-year observations must have at least 50 transactions to be included in the sample. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. The regression includes county-year-month and school district fixed effects; controls for bond characteristics including the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues.The baseline period for the district fixed effects is 2007.

A4 Extensions to the Structural Model

A4.1 Tax-Adjusted Municipal Bond 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

$$(1 - \tau_{s,t}) = (1 - \tau_t^{fed})(1 - \tau_{s,t}^{state}), \tag{A1}$$

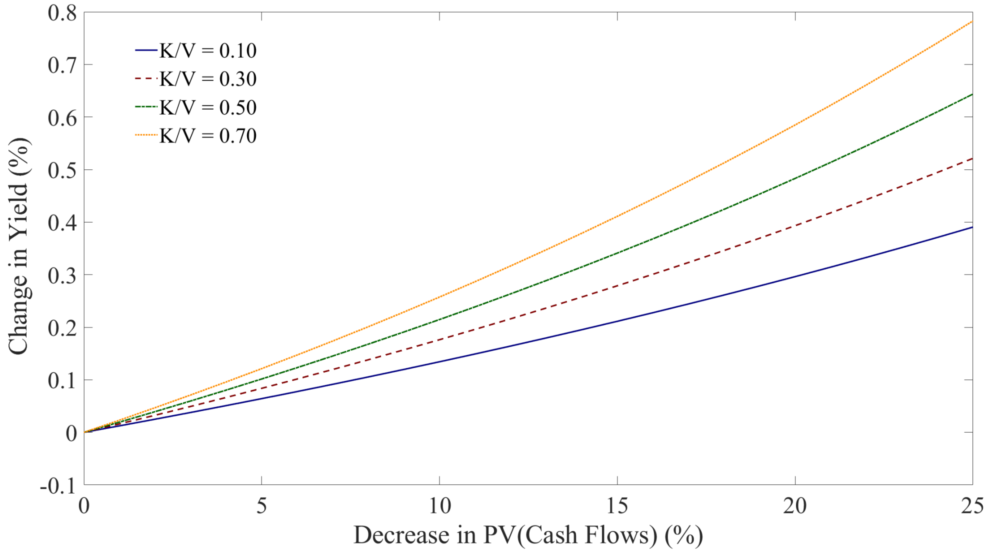
where τ_t^{fed} is the top federal income tax rate and $\tau_{s,t}^{state}$ is the top income tax rate in state s in year t. This formula accounts for the fact that state income tax payments are deductible from an individual's taxable income for federal taxes. Applying the tax adjustment and subtracting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

$$y_{i,t}^{TA} - r_t = \frac{y_{i,t}}{1 - \tau_{s,t}} - r_t. \tag{A2}$$

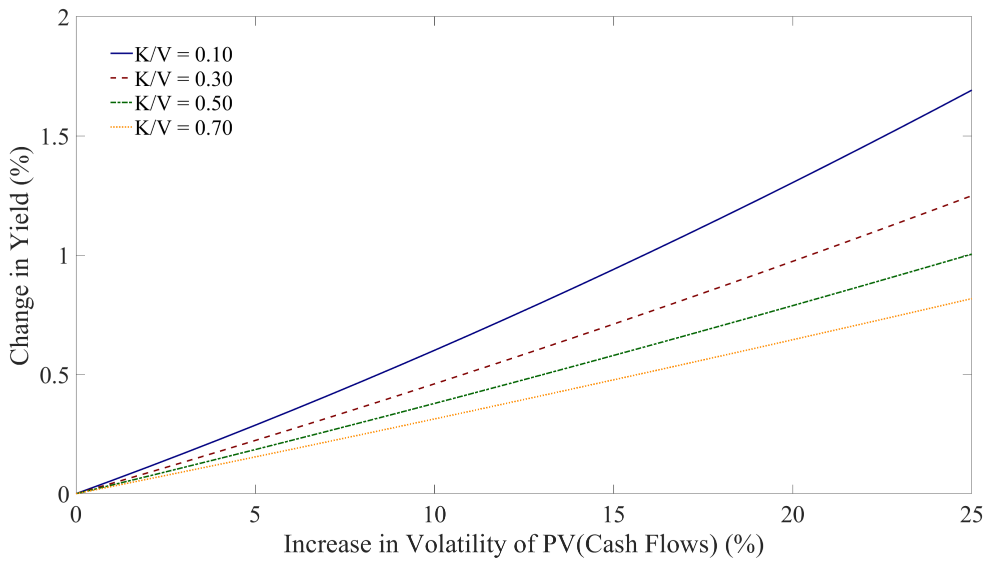
For simplicity, we use the top federal tax rate of 35% that prevailed for most of our sample period and the average top state tax rate of 5%. Figure A4 presents estimates based on tax-adjusted yields that are quantitatively similar to those reported in the paper.

Figure A4: Effects of Asset Value and Volatility Shocks – Tax-Adjusted 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. The other model parameters are: $y^{TA} = 5.25\%$ $r = 3.10\%$, and $T = 7.5$.

A4.2 Bankruptcy Costs and the Role of State Distress Policies

To assess the importance of state-level policies on municipal distress in mediating the effect of fundamental shocks on municipal bond yields, we extend the structural model to incorporate costs of financial distress. Specifically, we add a bankruptcy cost that reduces the asset value proportionally by a factor α in the event of default.

Suppose 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 the setup with a proportional bankruptcy cost α, the value of the bond is

$$D_\alpha = Ke^{-rT} - (1+\alpha)\left[Ke^{-rT}\Phi(-d_2) - V\Phi(-d_1)\right], \tag{A3}$$

where

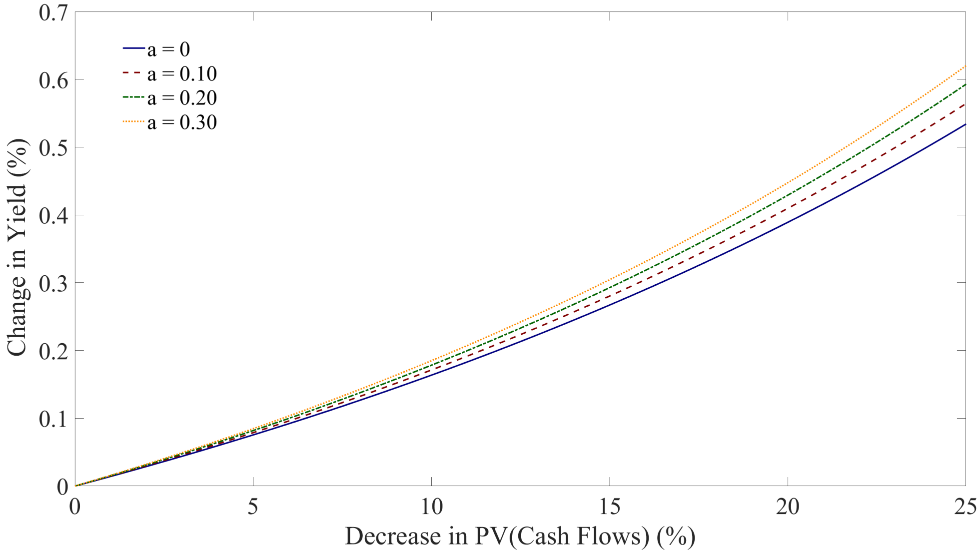
$$d_1 = \frac{\ln(V/K) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}, \quad d_2 = d_1 - \sigma\sqrt{T}. \tag{A4}$$

We use evidence on creditor recoveries in municipal defaults from Gao, Lee, and Murphy (2019) to calibrate an appropriate range of bankruptcy costs. These authors report average (median) recovery rates in default of 79% (89%) in states with proactive policies on municipal distress, 67% (72%) in states that allow municipalities to file for Chapter 9 bankruptcy, and 73% (77%) in states with no distress policy.

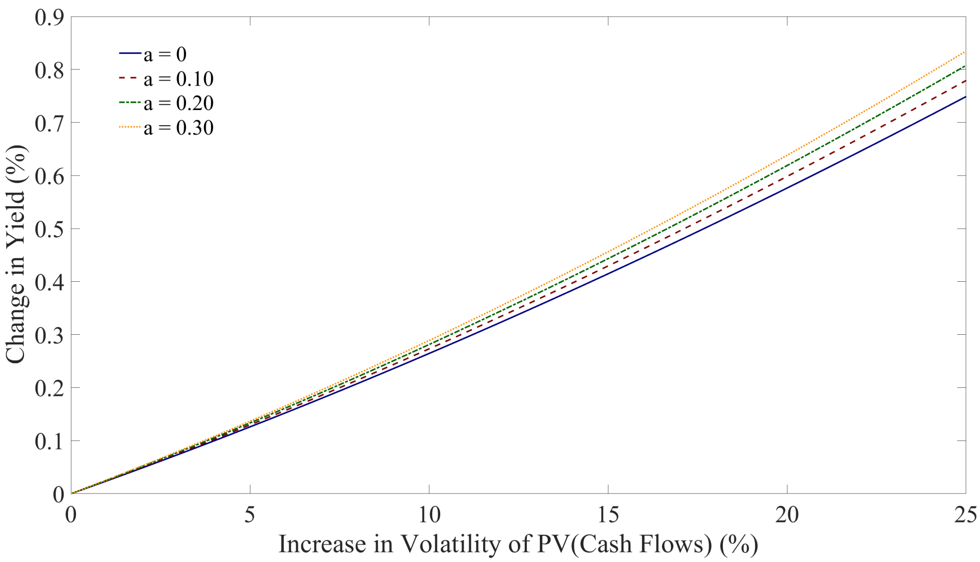
Figure A5 shows the effect of shocks to the underlying asset value and volatility when the bankruptcy cost is between zero and 30%, a range that encapsulates the dispersion in recovery rates documented by Gao, Lee, and Murphy (2019). The effects are larger when the bankruptcy cost is higher, but the differences are small: raising α from zero to 10% increases the effect of a 3% drop in asset values from 4.39 bps to 4.57 bps and the effect of a proportional 2% increase in volatility from 4.89 bps to 5.03 bps.

Figure A5: Effects of Asset Value and Volatility Shocks – Bankruptcy Costs

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 bankruptcy costs (α) of 0, 10%, 20%, and 30%, along with the associated model-implied volatilities. The other model parameters are: $y = 3.24\%$, $r = 2.68\%$, $K/V = 0.40$, and $T = 7.5$.

A4.3 Tiered Debt Structure with Senior Bank Loans

Ivanov and Zimmermann (2021) use regulatory data to document an upward trend in bank borrowing by municipal bond issuers. Bank loans are typically senior to municipal bonds but cannot be observed on public financial statements. In this section, we show that our conclusions are robust to the presence of senior loans on school district balance sheets.

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

$$B_\alpha = (1-\alpha)\left[V\left(\Phi(d_{1,S}) - \Phi(d_1)\right) - K_S e^{-rT}\left(\Phi(d_{2,S}) - \Phi(d_2)\right)\right] + K_J e^{-rT}\Phi(d_2), \qquad \text{(A5)}$$

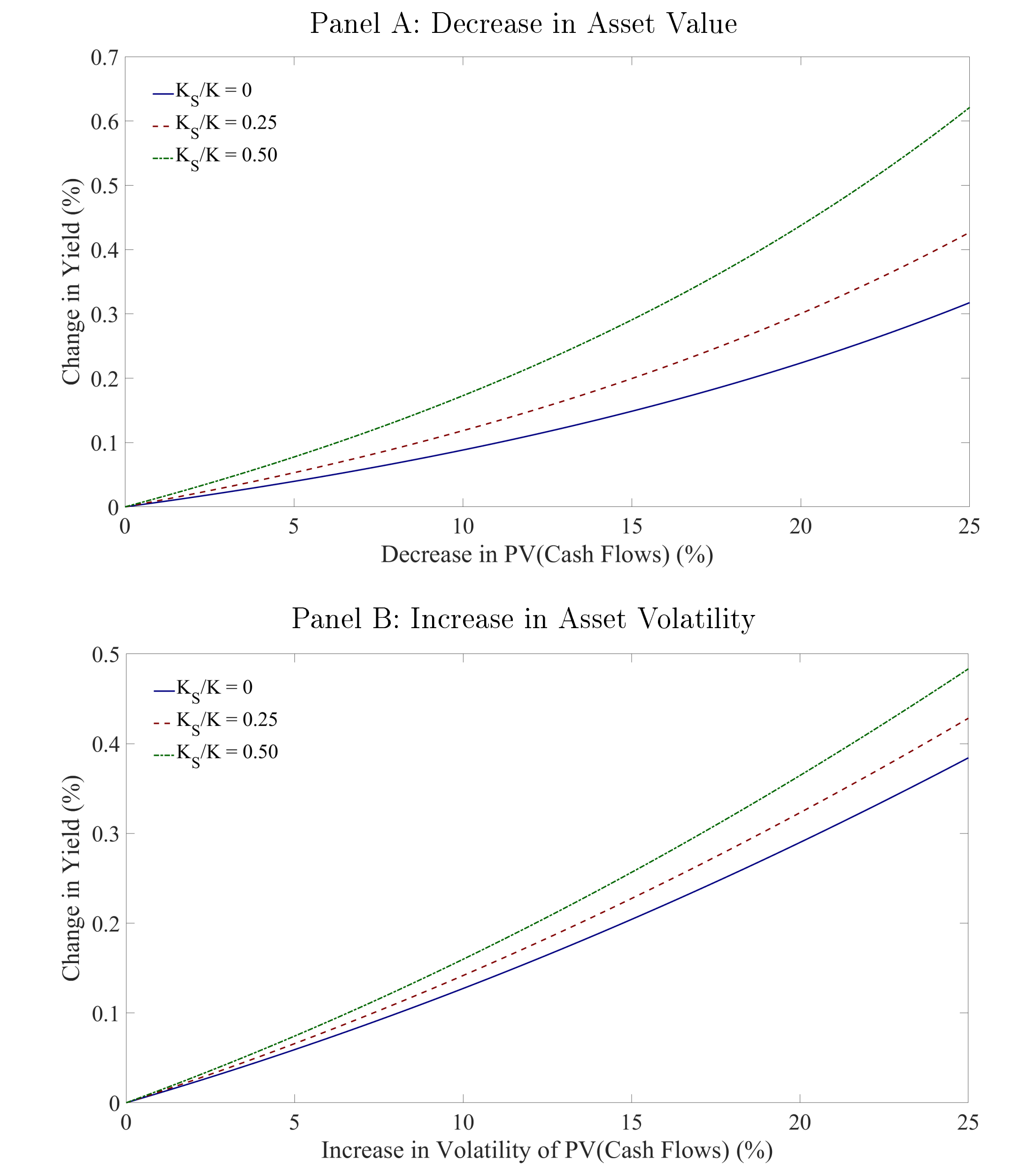
where

$$d_{1,S} = \frac{\ln\left(\frac{V}{\min\{K_S/(1-\alpha), K_S+K_J\}}\right) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}, \quad d_{2,S} = d_{1,S} - \sigma\sqrt{T} \qquad \text{(A6)}$$

and d_1 and d_2 are defined as in equation (A4).

Figure A6 shows the effect of shocks to the underlying asset value and volatility when the ratio of senior debt to total debt is equal to zero, 0.25, or 0.50. The effects are larger when the issuer has more senior debt due to the leverage effect on junior debt, but overall the estimates are qualitatively similar to those obtained from our baseline model.

Figure A6: Effects of Asset Value and Volatility Shocks – Tiered Debt Structure



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 ratios of senior debt to total debt equal to 0, 0.25, and 0.50, along with the associated model-implied volatilities. The other model parameters are: $y = 3.24\%$, $r = 2.68\%$, $K/V = 0.40$, $T = 7.5$, and $\alpha = 0$.

A5 Replication of Painter (2020)

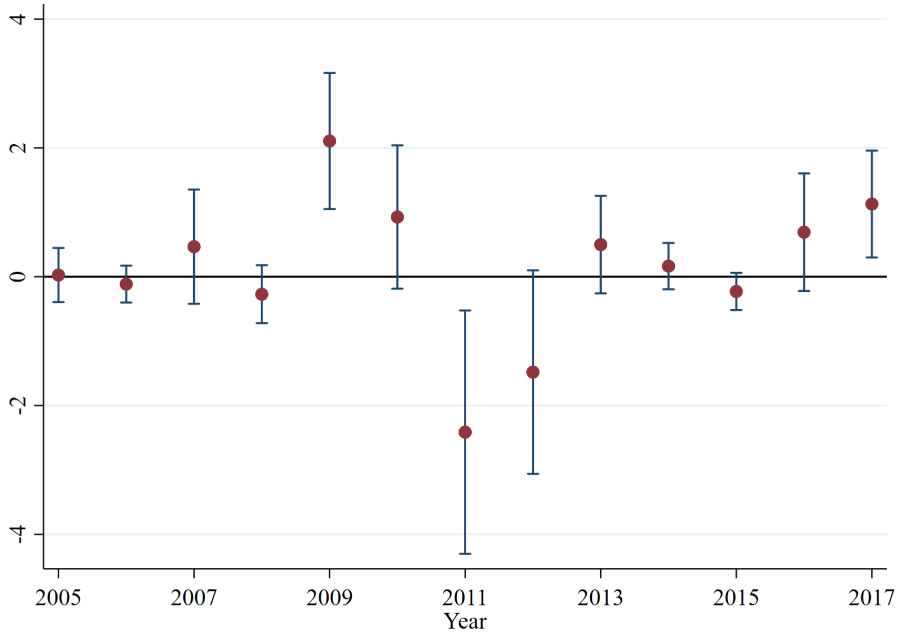
Painter (2020) finds that exposure to climate risk is associated with higher offering yields and gross spreads in the primary market for municipal bonds. His measure of climate risk exposure is based on Hallegatte et al. (2013), who estimate the expected annual loss from 40 cm (about 1.33 feet) of sea 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.

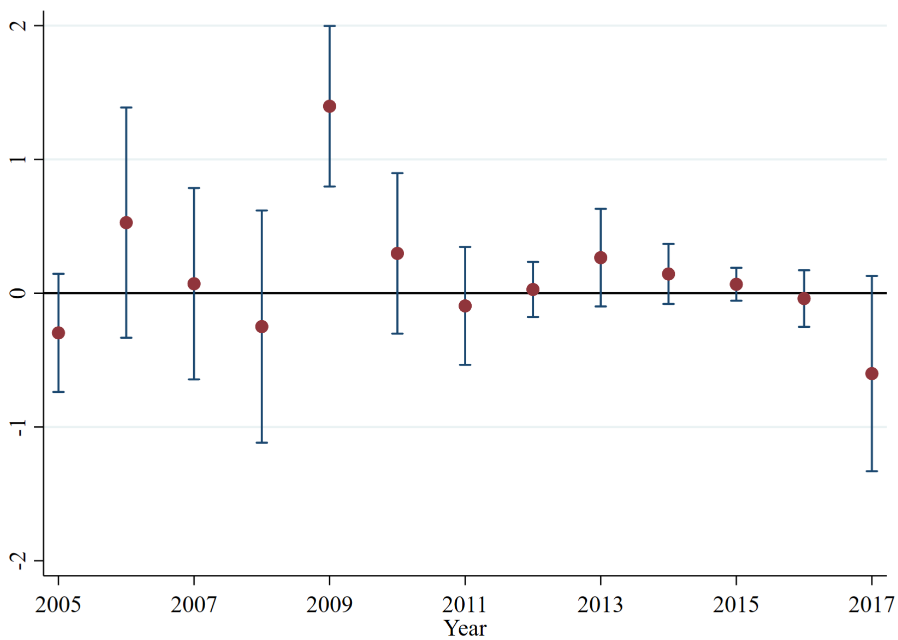
Figure A7 reveals that climate risk has the strongest effect in 2009, the last year of the recession that followed the financial crisis, for both long-maturity and short-maturity bonds. For long-maturity bonds, the climate risk coefficient is significantly negative in 2011 and positive in 2017. None 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 A7: 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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