

Sea Level Rise Exposure and Municipal Bond Yields*

Paul Goldsmith-Pinkham[†] Matthew T. Gustafson[‡] Ryan C. Lewis[§]
Michael Schwert[¶]

January 29, 2021

Abstract

Municipal bond markets begin pricing increased risk of sea level rise (SLR) exposure in 2013, coinciding with upward revisions of SLR projections. The effect is present across maturities, but larger for long-maturity bonds. We do not observe similar patterns using measures of immediate flood risk. We apply a structural model of credit risk to show that municipal bond investors expect a one standard deviation increase in SLR exposure to correspond to a reduction of 2% to 5% in the present value or an increase of 1% to 3% in the volatility of the local government cash flows supporting debt repayment.

*We thank Markus Baldauf, Asaf Bernstein, Sudheer Chava, Tony Cookson, Jess Cornaggia, Kimberly Cornaggia, Chitru Fernando, Stefano Giglio, Erik Gilje, Sara Holland, Yann Koby, James McCown, Rob Ready, Bill Schwert, Luke Taylor, and seminar participants at the University of Delaware, Wharton, the 2019 University of Oklahoma Energy and Commodities Finance Research Conference, and the 2021 American Finance Association meeting for helpful suggestions. We also thank Elaine Yao for excellent research assistance.

[†]Yale University; paul.goldsmith-pinkham@yale.edu.

[‡]Pennsylvania State University; mtg15@psu.edu.

[§]University of Colorado; ryan.c.lewis@colorado.edu.

[¶]The Wharton School, University of Pennsylvania; schwert@wharton.upenn.edu.

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 costs of SLR exposure and when they will manifest is important because they represent potential benefits of climate remediation that can be weighed against the costs of interventions.

In this paper, we examine how exposure to SLR risk is priced in the municipal bond market, 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 present value of future cash flows backing the bonds and the likelihood of negative shocks, 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 and traded in the same time period but varying 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. From 2014 to 2017, the last year four years of our sample, 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 basis point increase in municipal bond credit spreads, equivalent to 9% of the average spread in our sample.

To interpret the economic magnitude of our findings, we adapt the [Merton \(1974\)](#) model of credit risk to the municipal bond market.¹ We use the model to translate the estimated effects of SLR exposure on bond yields into implied changes in the future distribution of local government cash flows. After calibrating the model to match the average yield of municipal bonds in our sample, we find that our estimates are consistent with a reduction of 2% to 5% in the present value of the underlying cash flow stream, a proportional increase of 1% to 3% in the volatility of cash flows, or some combination of these effects, depending on the current condition of the issuer's balance sheet. The large economic consequence implied by a small increase in yields is due to the low unconditional default risk of municipal bonds. The estimated effects of SLR exposure on bond yields do not imply the expectation of catastrophic losses from climate-induced default, but they do suggest that investors anticipate a material economic impact of SLR risk on exposed municipalities.

To the extent that climate change is a salient risk to bondholders, the effect should be largest in longer-maturity bonds.² 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 the SLR exposure proxies for hurricane risk, then our results are consistent with a near-term increase in storm

¹ Although the [Merton \(1974\)](#) model has trouble matching the observed level of corporate credit spreads (e.g., [Huang and Huang \(2012\)](#)), [Schaefer and Strebulaev \(2008\)](#) show that it provides accurate predictions of the relation between changes in bond yields and underlying asset values, which is the goal of our exercise.

² This is true regardless of the channel (e.g., the possibility of coordinated migration due to expected chronic inundation, or worsening meteorological patterns).

frequency and probability.³ Adding controls for storm surge risk helps to disentangle these explanations. We find that the credit spread premium after 2012 is primarily attributable to SLR risk in both the full sample and at long maturities. The decomposition is inconclusive as to whether storm surge or SLR drive the jump in spreads for short-maturity bonds. Overall, the evidence is consistent with investors becoming more concerned about the long-run SLR exposure over time.

In our final set of tests, we provide evidence that an area's reliance on local property tax revenues to back school bonds and their reported level of concern about climate change are complementary mechanisms that influence the SLR exposure premium.⁴ This is consistent with existing literature showing that an area's beliefs with respect to climate change affects how SLR exposure is priced in real estate markets (see e.g., [Bernstein et al. \(2019\)](#) and [Baldauf et al. \(2020\)](#)). 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 et al. \(2017\)](#), [Berkman et al. \(2019\)](#), [Hong et al. \(2019\)](#)) and their cost of capital (e.g., [Sharfman and Fernando \(2008\)](#), [Chava \(2014\)](#), [Delis et al. \(2019\)](#)), as well as their operating performance (e.g., [Barrot and Sauvagnat \(2016\)](#), [Addoum et al. \(2020\)](#)) and financial policies (e.g., [Dessaint and Matray \(2017\)](#)). With respect to capital supply, research has shown that climate risk affects the allocation of credit by banks (e.g., [Cortés and Strahan \(2017\)](#), [Brown et al. \(2020\)](#)) and the beliefs of institutional investors ([Krueger et al. \(2020\)](#)). [Bennett and Wang \(2019\)](#) find that municipal bond issuance volumes and yields temporarily increase after natural disasters. [Baker et al. \(2018\)](#), [Flammer \(2020\)](#), and [Larcker and Watts \(2020\)](#) study the pricing of "green" bonds issued to fund environmentally friendly projects. [Giglio et al. \(2014\)](#) and [Giglio et al. \(2018\)](#) show that low discount rates should be used to discount the long-run risks of climate change. We contribute to this body of work by showing that the cost of debt financing depends on location-specific exposure to climate risk. This dependence is growing over time and implies that climate risk is expected to incur real economic costs on exposed issuers both in the near-term and over the long-run.

³Scientists predict an increase in severe tropical storms or hurricanes due to the warmer climate (e.g., [Webster et al. \(2005\)](#), [Holland and Bruyère \(2014\)](#), [Hayhoe et al. \(2018\)](#)).

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

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

An important contribution of this paper is to adapt a structural model of credit risk from the corporate finance literature to interpret the economic magnitude of the estimated effects of SLR exposure on coastal economies. Our model-based approach to evaluating the effects of SLR risk on borrowing costs is straightforward to apply in other situations where economic shocks affect the cost of risky debt issuance and can be used in non-corporate settings in which it may be difficult to observe the issuer's capital structure and the market value of its assets. We argue that theoretical models are a valuable source of discipline in the interpretation of reduced-form estimates, especially in settings where the underlying shock is difficult to quantify in dollar terms.⁵

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 bps 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.⁶ Our structural model suggests that this 23.4 bps estimate implies substantially more economic damage than im-

⁵In a recent working paper, [Boyer \(2019\)](#) 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 \(2019\)](#) 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 \(2019\)](#) focuses on state-level issuers for which balance sheet data are available.

⁶In 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).

plied by [Hallegatte et al. \(2013\)](#), on the order of a 20% 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 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-term and the 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 applies a structural model to interpret our empirical estimates. 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 seas 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 substantially, in large part due to the consideration of new environmental factors that substantially increased upper-bound estimates. Many scientists predict negligible SLR this century (e.g., [Hansen et al. \(2015\)](#)), but worst-case-scenario SLR projections have been increasing.

To quantify the evolution of SLR projections, we use information provided in [Garner et al. \(2018\)](#) to construct a panel of scientific papers that project global average SLR through 2100. [Garner et al. \(2018\)](#) highlight a total of 73 different reports from which we select a sample of comparable studies. Most studies model their SLR projections based on agreed-upon emissions scenarios, which change in 2012 with the release of Representative Carbon Pathways (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. To track the evolution of SLR

projections, we make assumptions on how long a particular study is considered “relevant.” In some cases, researchers update their analysis, so we simply use the latest update. For instance, when the IPCC releases its 2007 report, the 2001 report becomes obsolete. Other reports appear only once in our sample, in which case we assume a report is relevant for five years after the publication date. Finally, we equally weight across studies and scenarios to identify the average prediction and confidence bounds for each year from 2001 to 2017.⁷

Panel A of Figure 1 summarizes the evolution of sea level rise projections over our sample period. There is a noticeable upward trend in SLR projections, with the average forecast moving from less than two feet in 2001 to nearly four feet by 2017. There is a shift in projections beginning in 2007, with the best-case (1st percentile) scenario moving up sharply. We find a significant increase in the worst-case scenario forecasts beginning in 2012, when the 99th percentile of sea level rise projections moved from three feet to over four feet by 2013. Around the same time, a number of studies argued that the potential for glacial collapse in Antarctica may be significantly higher than previously thought. By the end of the sample period, the worst-case scenario involves over five feet of global SLR and the dispersion in forecasts is nearly four feet.⁸

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 Long- and Short-run Risks to Municipal Bond Investors

SLR exposure creates both long- and short-run inundation risks for exposed areas. In the long-run, rising oceans may eventually put coastal properties underwater, 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

⁷Internet Appendix Table A1 provides details on how we translate the results of each scientific study into a confidence bound for SLR projections. Most studies provide direct estimates of the probability distribution associated with their forecasts that follow an approximately normal distribution, as shown in Figure 5 of Garner et al. (2018). To compare across studies, we assume normality and use the distribution points provided by each study to determine the mean and standard deviation of its SLR forecast.

⁸This 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.

the future, as is the more severe flooding associated with coastal storms, such as hurricanes and nor'easters" (Hayhoe et al. (2018), pg. 74-75). Importantly, 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 et al. (2019), Baldauf et al. (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. 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.⁹ 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.¹⁰ 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 yields.

Our main prediction is agnostic as to whether it is long- or short-run inundation risk that

⁹"Indonesia will relocate capital from sinking Jakarta to Borneo," CBS News, August 27, 2019 ([Link](#)).

¹⁰"U.S. flood strategy shifts to 'unavoidable' relocation of entire neighborhoods," New York Times, August 26, 2020 ([Link](#)).

affects municipal bond yields. In either case, 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.

The long- and short-run risk channels differ with respect to the type of flood risk they predict will be most related to municipal bond yields. The short-run risk channel predicts that measures of short-term flood risk will be more powerful, while the long-run risk channel predicts the opposite. We test these predictions empirically by including measures of SLR exposure and current storm surge exposure in the same credit spread regression and comparing their coefficients.

Both the short- and long-run risks posed to municipal bond investors 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 in these instances.

2 Sample Construction and Identification Strategy

2.1 Sample Construction

Our empirical analysis studies the effect of SLR exposure on school district bond credit spreads. We focus on bonds issued by school districts for three reasons. First, 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 economic link between school districts' ability to repay debts and the anticipated effects of SLR on property values (Bernstein et al. (2019), Baldauf et al. (2020)). 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 2.2.

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 Rule-making 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 et al. (2007)).¹¹ We do not impose any restriction on the type of bond issued, as the vast majority of school districts issue general obligation bonds. Our results are robust to controlling for bond type across all of our specifications.

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

We restrict the sample to coastal watershed counties, as defined by the National Oceanic and Atmospheric Administration (NOAA), in states with an ocean shoreline.¹² Our process to determine the SLR exposure for each school district bond issuer in coastal counties closely follows Bernstein et al. (2019). First, we identify the location of each residential dwelling in the school district using the real estate assessor and transaction files in the Zillow Transaction and Assessment Dataset (ZTRAX). We then determine each property's SLR exposure using the 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.¹³

¹¹Internet Appendix Table A2 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.

¹²See coast.noaa.gov/htdata/SocioEconomic/NOAA_CoastalCountyDefinitions.pdf.

¹³Murfin and Spiegel (2020) argue that this exposure measure does not account for subsidence and therefore does not accurately capture SLR risk. NOAA acknowledges this in the SLR methodology: "[subsidence] effects are still

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 for six feet of SLR. Naturally, the region with six-foot exposure is larger and encompasses the three-foot exposure region. Finally, the red lines delineate school 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/green area and divide by the total number of dots in a district to obtain the fraction of properties exposed to chronic tidal flooding. We use the state and name of each school district to link the geographic exposure information to municipal bond issuers.¹⁴ 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 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.¹⁵

Finally, given that the link between local property values and the cash flows supporting repay-

sufficiently unknown that they may compound or offset each other in unpredictable ways, such that including only some processes may cause greater error than ignoring them.” In other words, the NOAA measure is based on more predictable and better understood factors, but may miss some less predictable aspects of SLR exposure.

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

¹⁵Internet Appendix Table A3 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.

ment of school bonds is central to our predictions, we exclude California from our main sample and analyze it separately from other states because California school bonds are less dependent on the local economy. California has a state-level organization, the California School Finance Authority (CSFA), that funds educational spending and insulates school districts from economic shocks. The CSFA 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-pooling features decrease the impact of local SLR shocks on municipal bondholders. The impact of SLR on California school districts is further dampened by Proposition 13, which caps property tax rates as a percentage of assessed value and the rate of assessment changes.¹⁶ 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 thereafter.

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 A4 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 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 bps over the AAA-rated benchmark curve. It has ten years to maturity, has aged four years since 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 bps to 261 bps relative to the MMA benchmark. The dispersion in spreads is narrow relative to other credit markets (e.g., corporate bonds) because of the low historical default rate in the municipal bond market.

¹⁶Wasi and White (2005) show that assessed property values have not kept pace with the market, resulting in subsidies of thousands of dollars per year for coastal homeowners.

2.2 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:

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

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 et al. \(2019\)](#) and [Baldauf et al. \(2020\)](#), we use six-foot SLR exposure as our primary measure of SLR risk. By the end of our sample period, most high-emissions SLR scenarios project a 99th percentile of over 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 et al. \(2019\)](#), 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 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 yields. 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 bond yields emerges or increases as SLR projections become more dire and salient, it is unlikely that the relation we observe is driven by omitted factors.

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.¹⁷ The yearly coefficients on Z_{bjt} control for time-varying factors that affect our estimates including the term structure of credit spreads, the issuer's option to call bonds before maturity, and the value of bond insurance (Cornaggia et al. (2020)). Other control variables X_{bjt} 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.

3 Empirical Results

3.1 Effect of SLR Exposure on Bond Yields

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

¹⁷We 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.

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 closer to the water having other confounding features (e.g., higher real estate values) that could lead to lower credit spreads.

We find little evidence that the relationship 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 our sample in 2017, the coefficients become more statistically significant and range from 3.9 to 5.9 across the three columns. These coefficients suggest that a one standard deviation increase in SLR exposure predicts a 4 to 6 basis point increase in municipal credit spreads. Compared to the average yield spread in our sample of 57 basis points, this estimate suggests that a one standard deviation in SLR exposure results in a 7% to 10% increase in municipal bond yield 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 most recent jump in 2014 leading to statistically significant coefficients. This rise in the SLR exposure premium around 2014 coincides with the evidence in Figure 1, which shows a spike in SLR projections in the scien-

tific 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 2007.¹⁸

Internet Appendix Table A4 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.

3.2 Evidence on the Economic Mechanism

In this section, we consider whether the long- or short- run risk channels discussed in Section 1.2 are likely drivers of the SLR exposure premium.

We first examine whether the SLR exposure premium relates to bond maturity. Although bonds of all maturities may be influenced by SLR risk, 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 the bond's maturity is less than or greater than ten years. Approximately 42% of our 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 in both subsamples.

As we discuss in Section 1.2, the SLR exposure credit spread 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

¹⁸Although we use different data and a different measure of exposure in our analysis, we provide evidence in the Internet Appendix based on the new issue data 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.

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.

The main difference in the empirical predictions of the long- and short-run risk hypotheses is the type of flood risk that matters most in determining municipal credit spreads. The long-run risk hypothesis predicts that a long-run SLR exposure measure is a more powerful predictor than a short-run flood risk measure, while the short-run risk hypothesis predicts the opposite.¹⁹ To examine the relative importance of these hypotheses, we introduce a measure of short-term flood risk in the form of storm surge exposure. 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).²⁰

Table 4 augments our regression with this measure of storm surge exposure. Column (1) is based on the full sample, column (2) the long-maturity sample, and column (3) the short-maturity sample. 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. A caveat to the partitioned analyses in columns (2) and (3) is that we may 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, our proxy for long-run SLR risk, ap-

¹⁹Notably, these predictions say little about whether short- or long-run flood risk matters more for municipal bond credit spreads. Rather, they speak to which type of risk has become relatively more important as climate change predictions have become more dire.

²⁰The 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 positively correlated with a correlation of 0.83. Differences between the measures depend on the local geography. For instance, areas on either side of a peninsula will have similar SLR exposure, but may have very different storm surge exposure depending on their relative exposure to hurricane-force winds.

appears to be a more important driver of the SLR exposure premium than storm surge exposure, our proxy for short-term flood risks. However, this conclusion applies mostly to long-maturity bonds. More statistical power is necessary to determine the relative importance of short- and long-run risks in driving the observed effects of SLR exposure on short-maturity bond spreads.

3.3 What Drives the Response to SLR Risk? Tax Reliance and Local Beliefs

In this section, we examine two complementary channels through which SLR exposure could impact bond yields. First, as discussed in Section 2, in most cases local property taxes are the primary source of school funding. This creates a direct link between expected future real estate losses 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 5 presents our 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.²¹ We find that states with higher property tax rates experience larger credit spread increases in SLR exposed districts. To address the potential 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.²² We find that the school district bonds exposed to SLR have had the largest increases in credit spreads when those districts are most dependent on local revenues to fund operations.

A limitation to the preceding proxies for a district's property tax dependence is that even if property taxes make up the majority of the revenue base, they may not actually respond on the margin (e.g., there may be an expectation of state bailouts). To examine this possibility we introduce data from California, which until this point we have excluded from our sample due to 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 and the CSFA acts to pool risk across school districts. Column (3) replicates our main analysis using California school districts and finds a statistically insignif-

²¹See <https://files.taxfoundation.org/20200225111115/Facts-Figures-2020-How-Does-Your-State-Compare.pdf>.

²²See <https://www.everycrsreport.com/reports/R45827.html>.

ificant coefficient on SLR exposure after 2012. Thus, in a sample with 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.

Prior research shows that house prices are negatively impacted by exposure to sea level rise, especially in recent years (Bernstein et al. (2019), Baldauf et al. (2020)). Therefore, a natural question is whether the yield effects we observe are a direct result of lower house prices. In column (4), we add the district-level log median house price by calendar quarter as a control and find that intuitively, higher house prices correspond to lower municipal bond spreads. However, this control does not meaningfully change the post-2012 SLR exposure coefficient relative to our yearly estimates in Table 2. This suggests that our findings are not driven by a downward shift in the level of house prices, but they could reflect within-district heterogeneity in price changes or greater uncertainty about the future path of real estate values. Section 4 explores the latter possibility using a structural model of credit risk.

A second channel through which SLR could impact credit spreads is investors' beliefs about climate risk. Bernstein et al. (2019) and Baldauf et al. (2020) find that climate change beliefs affect how real estate markets price SLR exposure. It is reasonable to expect that local beliefs will also matter for municipal bond pricing because buyers are often local retail investors due to the tax advantages of in-state ownership. To measure an area's beliefs about climate change, we merge our data with the Yale Climate Opinions map data (Howe et al. (2015)). Specifically, we aggregate 2014 county-level survey data on responses to the question "worried about global warming" to the state level, weighting each county by the number of school districts it houses. We aggregate to the state level instead of using the county-level data directly because the segmentation of municipal bond investors is driven by state-level tax policy. To form our State Worry measure, we then subtract the average state's level of worry and divide by the standard deviation, resulting in a standardized measure that ranges from -2.39 to 0.87.

In columns (1) and (2) of Table 6 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 6 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 2013-2017 period, and the state's level of worry about climate change. Consistent with columns (1) and (2), we find that the post-2012 SLR exposure premium is significantly larger in worried states relative to less worried states.

Taken together, the evidence in this section suggests that SLR exposure has become a significant positive predictor of municipal bond yield spreads since 2013. Consistent with the SLR exposure premium being due to increasingly dire climate change projections, it emerges at the same time as scientific studies project more significant future SLR. Our findings are consistent with there being both long- and short-run climate change risks at play. We find effects on short- and long-maturity bonds, but we find larger effects on long-maturity bonds and the effects on these long-maturity bonds are related to SLR exposure, but not immediate flood risks. We also show that reliance on local property taxes and local beliefs regarding future climate change are complementary mechanisms through which increased SLR exposure has begun to affect municipal bond spreads.

4 Interpretation of Magnitudes

4.1 Structural Model of Municipal Credit Risk

The estimates presented in the previous section reveal a statistically significant effect of SLR exposure on municipal borrowing costs. We estimate that a one standard deviation increase in SLR exposure is associated with an increase in municipal bond credit spreads of approximately 5 basis points at the end of our sample period. Interpreting the credit spread as the risk-neutral expected loss rate from default (Duffie and Singleton (1999)), the estimated effect implies a small increase in the expected loss rate of exposed issuers relative to unexposed issuers.²³ However, the unconditional risk of default in the municipal bond market is very low, so small increases in credit spreads could correspond to material changes in the underlying fundamentals. In this section, we

²³Credit spreads depend on the probability of default and the expected loss given default. Higher municipal bond spreads could be due to a higher likelihood of default, lower expected recoveries in default, or both. We do not take a stand on the relative contributions of these channels because we cannot distinguish among them with available data.

use a structural model of credit risk based on Merton (1974) to provide economic context for the magnitude of our estimates. The model allows us to quantify the expected impact of shocks to the present value and volatility of municipal cash flows on the yields of municipal bonds.

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 very similar to the corporate context. The source of debt repayment is a cash flow stream that depends on tax revenues, expenditures, and intergovernmental transfers. The present value of these cash flows, which we refer to as the asset value, is equivalent to the market value of a firm in the standard discounted cash flow framework.²⁴

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 this basic setup, the value of the bond is

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

where

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

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

²⁴If the issuer were to default, bondholders would have a claim on the future stream of revenues and would recover an amount determined in a Chapter 9 bankruptcy proceeding. From the perspective of creditors, the main difference between municipal and corporate bankruptcy is that asset liquidation cannot be forced by creditors under Chapter 9. However, the assets of a firm derive their value from the ability to generate cash flows, so this distinction is really about managerial agency and corporate control, which are outside of the model.

credit spread interchangeably, as we are holding the risk-free rate fixed in our analysis.²⁵

Before proceeding, we should provide some context for this exercise. With few exceptions (e.g., [Gray et al. \(2007\)](#), [Boyer \(2019\)](#)), 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 consisting of credit and non-credit components:

$$D = D_C + D_{NC}. \quad (5)$$

[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

²⁵The credit risk framework considered here is usually applied to taxable corporate bond yields. Our calculation of the model parameters implied by municipal bond yields accounts for the tax exemption's effect on the pricing of credit risk. In the Internet Appendix, we obtain quantitatively similar estimates performing the model analysis on tax-adjusted yields as in [Schwert \(2017\)](#), using the LIBOR interest rate swap curve as the risk-free benchmark.

bonds. Since the default risk of municipal bonds also depends on the dynamics of an underlying cash flow stream, we expect the same result to hold in this setting.²⁶ In contrast to [Schaefer and Strebulaev \(2008\)](#), who study the relation between a firm's 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 by controlling for liquidity proxies and time-varying county-level economic conditions.²⁷

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

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

$$B_\alpha = (1 - \alpha) \left[V(\Phi(d_{1,S}) - \Phi(d_1)) - K_S e^{-rT} (\Phi(d_{2,S}) - \Phi(d_2)) \right] + K_J e^{-rT} \Phi(d_2), \quad (6)$$

where

$$d_{1,S} = \frac{\ln \left(\frac{V}{\min\{K_S/(1-\alpha), K_S+K_J\}} \right) + (r + \frac{1}{2}\sigma^2) T}{\sigma\sqrt{T}}, \quad d_{2,S} = d_{1,S} - \sigma\sqrt{T} \quad (7)$$

²⁶It 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.

²⁷Although 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 et al. \(2004\)](#)) suggests it performs poorly at capturing term structure effects. This is in part due to the model's parsimonious specification of interest rate dynamics.

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

In untabulated analysis, we consider an alternative model with downward jumps in the underlying asset value that could reflect the occurrence of natural disasters or discontinuous revisions in the expected impact of climate change. Although this model leads to similar intuition regarding the economic impact of sea level rise exposure, we prefer the model without jumps because it has fewer parameters, which makes it easier to calibrate and to interpret. Moreover, its ability to capture the credit component of yield changes is supported in the literature, whereas the model with jumps does not enjoy the same empirical support.

4.2 Model Calibration and Predictions

Our objective is to estimate the yield change for a typical municipal bond following a shock to the distribution of the issuer's cash flows. Table 1 indicates that the mean bond in our sample has a yield-to-maturity of 3.24%, which corresponds to a credit spread of 56 bps 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. We consider other specifications to shed light on the robustness of our predictions and relate our estimates to the magnitudes in related work by [Painter \(2020\)](#).

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 range of leverage ratios (K/V in the model) and asset volatilities (σ) to match the typical bond yield in the data. To obtain an appropriate set of leverage and volatility pairs, we back out the model-implied asset volatility for leverage ratios ranging from 1% to 99%. Figure 6 shows that the implied volatility is decreasing in leverage, which is intuitive given that the calibration holds yield fixed.

We use these parameter values to compute the model-implied effects of adverse changes in the present value of cash flows (i.e., the underlying asset value) or the volatility of the underlying asset value on the yield-to-maturity of a municipal bond. 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.

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

Panel C of Figure 7 presents the combination of asset value and volatility shocks that correspond to our estimated 5 bps increase in municipal bond yields. Naturally, a larger shock to asset value implies a smaller shock to volatility, and vice versa, holding the change in yield fixed.

Table 7 reports model-implied changes in yield based on alternative specifications including bankruptcy costs or senior debt, which suggests that our conclusions are robust to the model specification and the possible presence of bank loans on the issuer's balance sheet. In general, large shocks to the underlying cash flow stream are necessary to generate non-trivial increases in yield, given the low level of credit risk in this market.

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

The right two columns of Table 7 use these parameters to predict the change in yield resulting from shocks to the value or volatility of the underlying cash flows. For the typical bond, we find that a 1% drop in the underlying asset value, which is equivalent to a 1% drop in annual GDP

under the assumption that tax receipts as a fraction of GDP are held fixed, corresponds to only a 0.7 bps increase in yield-to-maturity. The model implies that a drop in annual GDP of about 20% is necessary to cause a yield increase of more than 20 bps, even for bonds in the 90th percentile of the credit spread distribution. Intuitively, the implied shock to volatility is smaller, with a 10% proportional increase generating a yield increase of 28 bps for the typical long-maturity bond.

Panel D of Figure 7 provides a visual depiction of the combination of shocks to the asset value and volatility necessary to produce a 23.4 bps increase in yield under the model specification based on the average long-term municipal bond yield. 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%. We conclude that the estimates in Painter (2020) imply an economic impact that is an order of magnitude larger than the reduction in annual GDP used as his measure of climate risk, consistent with exposure to the Great Recession affecting his results.

4.3 Discussion

What does the model imply about the economic magnitudes from our analysis of municipal bond credit spreads? We estimate that a one standard deviation increase in the number of properties exposed to six feet of sea level rise corresponds to a 5 bps increase in credit spreads for coastal school districts. Under the baseline model calibration, this effect is in line with a reduction of 2% to 5% in the present value of the underlying cash flow stream or a proportional increase of 1% to 3% in the volatility of cash flows, depending on the issuer's leverage and corresponding baseline volatility. Although the estimated effects of SLR exposure on bond prices do not imply large expected losses from climate-induced default, they do suggest that the municipal bond market is pricing a material economic impact of SLR risk on exposed issuers.

The effect of SLR exposure on the present value of cash flows could be driven by changes in expected cash flows or by movements in discount rates. On its own, the model cannot distinguish between these channels, but there are reasons to believe that our estimates reflect changes in expected cash flows rather than changes in discount rates. Recall that the estimated effect on bond prices is from a difference-in-differences regression framework in which we compare the credit spreads of exposed and unexposed issuers in the same county. Additionally, the marginal

investor in the municipal bond is likely to be diversified against any idiosyncratic SLR risk. Thus, systematic risk needs to have increased differentially for exposed issuers relative to the start of the sample for discount rates to explain our findings. Nevertheless, we urge caution in interpreting the output of our model as exclusively driven by changes in cash flows.

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

With regard to pensions, most states fund teachers' retirement plans at the state level, so it is unlikely that pension funding has a differential effect on SLR exposed and unexposed school districts in the same county. If pension funding were directly affecting our estimates, then we would expect to see large effects during the financial crisis, 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 attenuation bias from bailouts discussed above.

5 Conclusion

This paper uses the municipal bond market to study the extent to which the risk of sea level rise is priced in financial markets. In line with the evolution of scientific consensus and popular concern about this risk, we find that the market does not change its pricing of SLR until 2013, after which we observe that exposed issuers have significantly higher borrowing costs than unexposed issuers. After 2013, a one standard deviation increase in SLR exposure corresponds to a 5 bps 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, an important contribution of this paper is to adapt a structural model of credit risk from the corporate finance literature to interpret the economic magnitude of the estimated effects. 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% to 5% in the present value of local government cash flows or a proportional increase of 1% to 3% in the volatility of these cash flows. These estimates shed light on the value that could be unlocked by climate remediation efforts in coastal communities. 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.

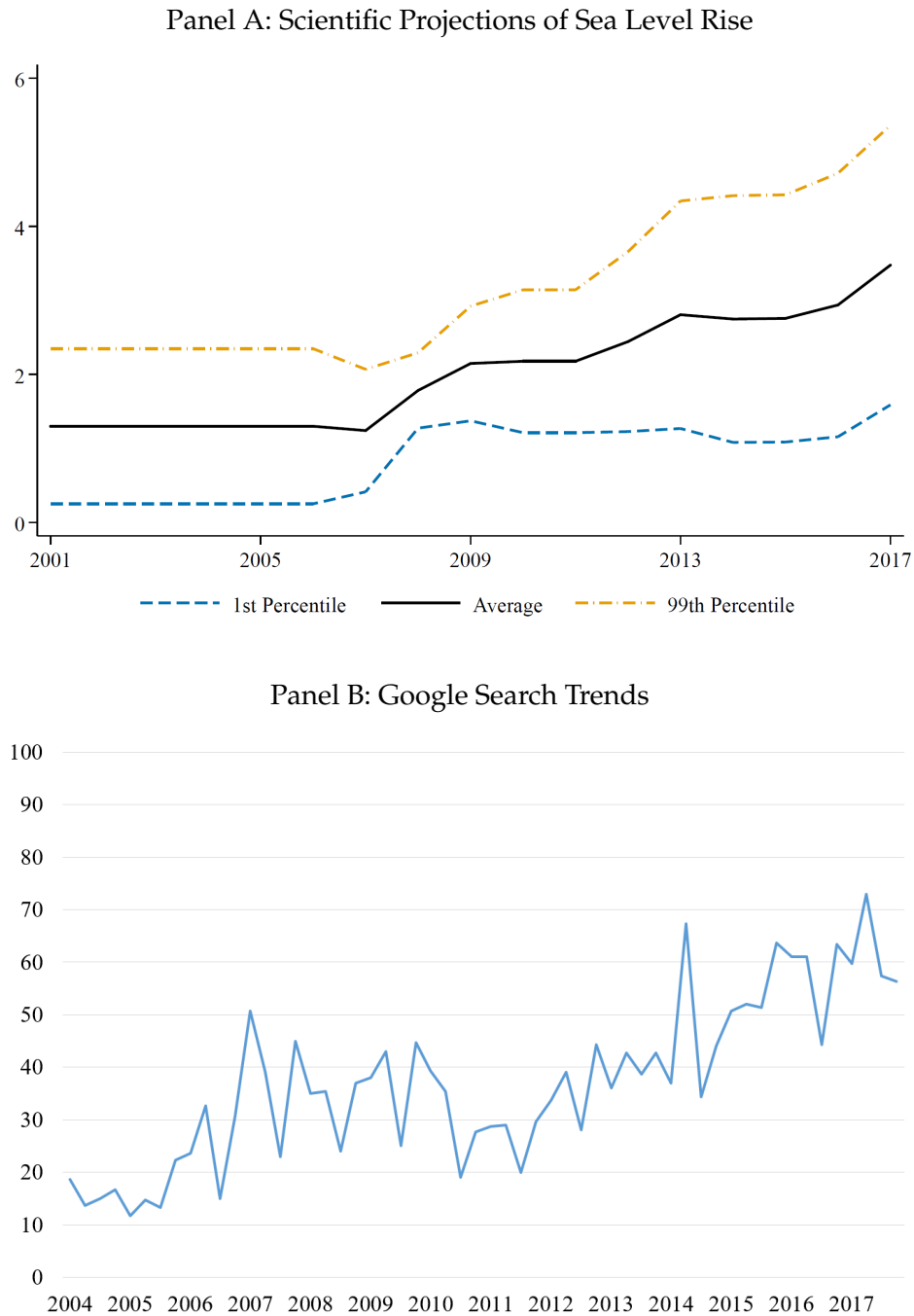
References

- Addoum, Jawad M., David T. Ng, and Ariel Ortiz Bobea, 2020, Temperature shocks and establishment sales, *Review of Financial Studies* 33, 1331–1366.
- Baker, Malcolm P., Daniel Bergstresser, George Serafeim, and Jeffrey Wurgler, 2018, Financing the response to climate change: The pricing and ownership of u.s. green bonds, *SSRN 3275327*.
- Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis, 2020, Does climate change affect real estate prices? only if you believe in it, *Review of Financial Studies* 33, 1256–1295.
- Bansal, Ravi, Dana Kiku, and Marcelo Ochoa, 2017, Price of long-run temperature shifts in capital markets.
- Barrot, Jean-Noël, and Julien Sauvagnat, 2016, Input specificity and the propagation of idiosyncratic shocks in production networks, *Quarterly Journal of Economics* 131, 1543–1592.
- Bennett, Benjamin, and Zexi Wang, 2019, Costs of natural disasters in public financing, *SSRN 3359694*.
- Berkman, Henk, Jonathan Jona, and Naomi S. Soderstrom, 2019, Firm-specific climate risk and market valuation, *SSRN 2775552*.
- Bernstein, Asaf, Matthew Gustafson, and Ryan Lewis, 2019, Disaster on the horizon: The price effect of sea level rise, *Journal of Financial Economics* 134, 253–272.
- Boyer, Chuck, 2019, Public pensions and state government borrowing costs, Working paper.
- Brown, James R., Matthew Gustafson, and Ivan Ivanov, 2020, Weathering cash flow shocks, *Journal of Finance* forthcoming.
- Chalmers, John M.R., 1998, Default risk cannot explain the muni puzzle: Evidence from municipal bonds that are secured by u.s. treasury obligations.
- Chava, Sudheer, 2014, Environmental externalities and cost of capital, *Management Science* 60, 2223–2247.
- Church, John A., and Neil J. White, 2006, A 20th century acceleration in global sea-level rise, *Geophysical Research Letters* 33.
- Cornaggia, Kimberly R., John Hund, and Giang Nguyen, 2020, The price of safety: The evolution of municipal bond insurance value, *SSRN 3266890*.
- Cortés, Kristle Romero, and Philip E. Strahan, 2017, Tracing out capital flows: How financially integrated banks respond to natural disasters, *Journal of Financial Economics* 125, 182–199.
- DeConto, Robert M., and David Pollard, 2016, Contribution of antarctica to past and future sea-level rise, *Nature* 531, 591.
- Delis, Manthos D., Kathrin de Greiff, and Steven Ongena, 2019, Being stranded with fossil fuel reserves? climate policy risk and the pricing of bank loans, *SSRN 3125017*.
- Dessaint, Olivier, and Adrien Matray, 2017, Do managers overreact to salient risks? evidence from hurricane strikes, *Journal of Financial Economics* 126, 97–121.
- Duffie, Darrell, and Kenneth J. Singleton, 1999, Modeling term structures of defaultable bonds, *Review of Financial Studies* 12, 687–720.
- Eom, Young Ho, Jean Helwege, and Jing-Zhi Huang, 2004, Structural models of corporate bond pricing: An empirical analysis, *Review of Financial Studies* 17, 499–544.
- Flammer, Caroline, 2020, Corporate green bonds, *SSRN 3125518*.
- Garner, Andra J., Jeremy L. Weiss, Adam Parris, Robert E. Kopp, Radley M. Horton, Jonathan T. Overpeck, and Benjamin P. Horton, 2018, Evolution of 21st century sea level rise projections, *Earth's Future* 6, 1603–1615.

- Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebe, and Andreas Weber, 2018, Climate change and long-run discount rates: Evidence from real estate.
- Giglio, Stefano, Matteo Maggiori, and Johannes Stroebe, 2014, Very long-run discount rates, *Quarterly Journal of Economics* 130, 1–53.
- Gray, Dale F., Robert C. Merton, and Zvi Bodie, 2007, Contingent claims approach to measuring and managing sovereign credit risk, *Journal of Investment Management* 5, 5–28.
- Green, Richard C., Burton Hollifield, and Norman Schurhoff, 2007, Dealer intermediation and price behavior in the aftermarket for new bond issues, *Journal of Financial Economics* 86, 643–682.
- Hallegatte, Stephane, Colin Green, Robert J. Nicholls, and Jan Corfee-Morlot, 2013, Future flood losses in major coastal cities, *Nature Climate Change* 3, 802.
- Hansen, Jens Morten, Troels Aagaard, and Antoon Kuijpers, 2015, Sea-level forcing by synchronization of 56-and 74-year oscillations with the moon's nodal tide on the northwest european shelf (eastern north sea to central baltic sea), *Journal of Coastal Research* 31, 1041–1056.
- Hayhoe, Katharine, Donald J. Wuebbles, David R. Easterling, David W. Fahey, Sarah Doherty, James P. Kossin, William V. Sweet, Russell S. Vose, and Michael F. Wehner, 2018, Our changing climate, in David R. Reidmiller, Christopher W. Avery, David R. Easterling, Kenneth E. Kunkel, Kristin L.M. Lewis, Thomas K. Maycock, and Brooke C. Stewart, eds., *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment*, volume II, 72–144 (U.S. Global Change Research Program, Washington, DC, USA).
- Holland, Greg J., and Cindy L. Bruyère, 2014, Recent intense hurricane response to global climate change, *Climate Dynamics* 42, 617–627.
- Hong, Harrison, Frank Weikai Li, and Jiangmin Xu, 2019, Climate risks and market efficiency, *Journal of Econometrics* 208, 265–281.
- Howe, Peter D., Matto Mildener, Jennifer R. Marlon, and Anthony Leiserowitz, 2015, Geographic variation in opinions on climate change at state and local scales in the usa, *Nature Climate Change* 5, 596–603.
- Huang, Jing-Zhi, and Ming Huang, 2012, How much of the corporate-treasury yield spread is due to credit risk?, *Review of Asset Pricing Studies* 2, 153–202.
- Ivanov, Ivan, and Tom Zimmermann, 2019, The privatization of municipal debt, SSRN 3056079 .
- Krueger, Philipp, Zacharias Sautner, and Laura T. Starks, 2020, The importance of climate risks for institutional investors, *Review of Financial Studies* 33, 1067–1111.
- Larcker, David F., and Edward M. Watts, 2020, Where's the greenium?
- Marcy, Doug, Nate Herold, Kirk Waters, William Brooks, Brian Hadley, Matt Pendleton, Keil Schmid, Mike Sutherland, Kyle Dragonov, John McCombs, and Sean Ryan, 2011, New mapping tool and techniques for visualizing sea level rise and coastal flooding impacts., In *Proceedings of the 2011 Solutions to Coastal Disasters Conference*, Anchorage, Alaska 474–490.
- Merton, Robert C., 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* 29, 449–470.
- Murfin, Justin, and Matthew Spiegel, 2020, Is the risk of sea level rise capitalized in residential real estate?
- Novy-Marx, Robert, and Joshua D. Rauh, 2012, Fiscal imbalances and borrowing costs: Evidence from state investment losses.
- Painter, Marcus, 2020, An inconvenient cost: The effects of climate change on municipal bonds, *Journal of Financial Economics* 135, 468–482.
- Schaefer, Stephen M., and Ilya A. Strebulaev, 2008, Structural models of credit risk are useful: Evidence from hedge ratios on corporate bonds, *Journal of Financial Economics* 90, 1–19.

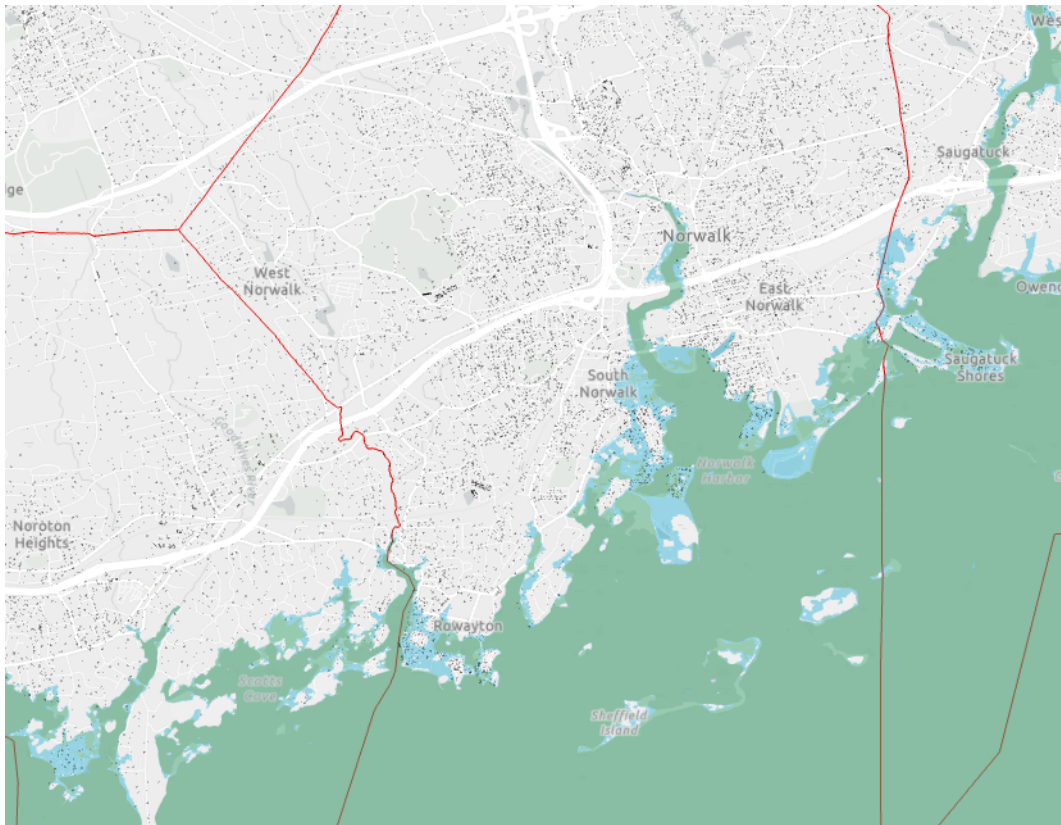
- Schultz, Paul, 2012, The market for new issues of municipal bonds: The roles of transparency and limited access to retail investors, *Journal of Financial Economics* 106, 492–512.
- Schwert, Michael, 2017, Municipal bond liquidity and default risk, *Journal of Finance* 72, 1683–1722.
- Schwert, Michael, 2020, Does borrowing from banks cost more than borrowing from the market?, *Journal of Finance* 75, 905–947.
- Sharfman, Mark P., and Chitru S. Fernando, 2008, Environmental risk management and the cost of capital, *Strategic Management Journal* 29, 569–592.
- Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P.M. Midgley, eds., 2013, *Summary for Policymakers*, book section SPM, 1–30 (Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA).
- Sweet, William V., Robert E. Kopp, Christopher P. Weaver, Jayantha Obeysekera, Radley M. Horton, E. Robert Thieler, and Chris Zervas, 2017, Global and regional sea level rise scenarios for the united states .
- Wasi, Nada, and Michelle J White, 2005, Property tax limitations and mobility: The lock-in effect of california’s proposition 13, Working Paper 11108, National Bureau of Economic Research.
- Webster, Peter J., Greg J. Holland, Judith A. Curry, and H.R. Chang, 2005, Changes in tropical cyclone number, duration, and intensity in a warming environment, *Science* 309, 1844–1846.

Figure 1: Time Series of Sea Level Rise Projections and 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 scaled to 100. We average the monthly data over each calendar quarter to smooth out high-frequency fluctuations in the series.

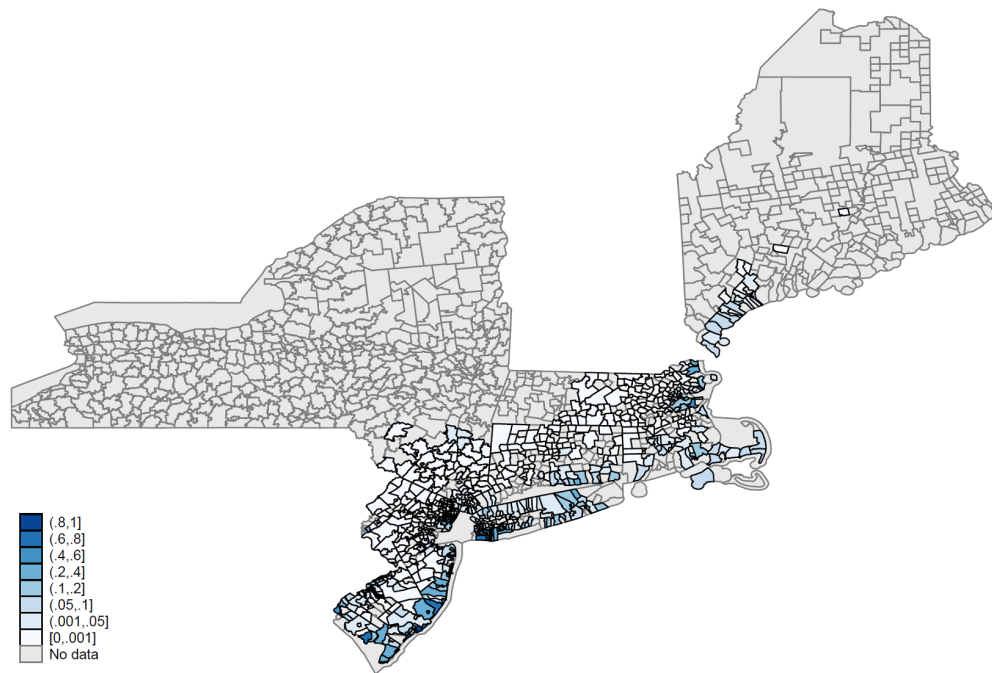
Figure 2: Sea Level Rise Exposure in Fairfield County, Connecticut



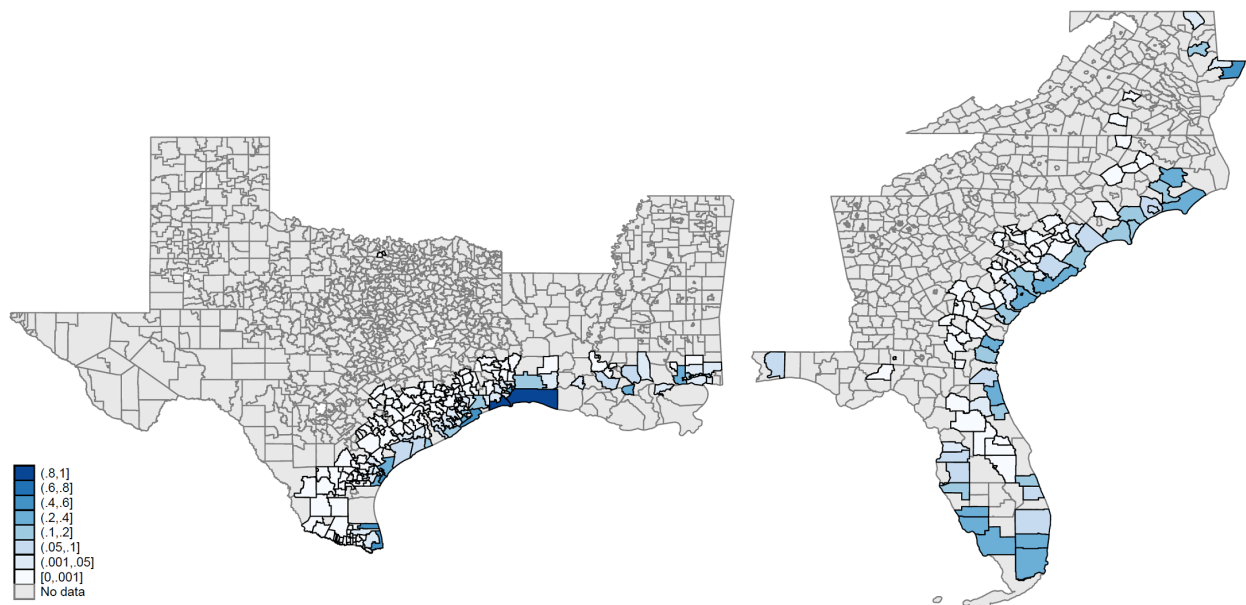
Note: This figure maps housing locations and exposure to sea level rise for a portion of Fairfield County, Connecticut. Black dots are residential dwelling units, the green area is the three-foot NOAA SLR scenario, the light blue area is the six-foot scenario, and the red lines delineate school districts.

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

Panel A: Northeast

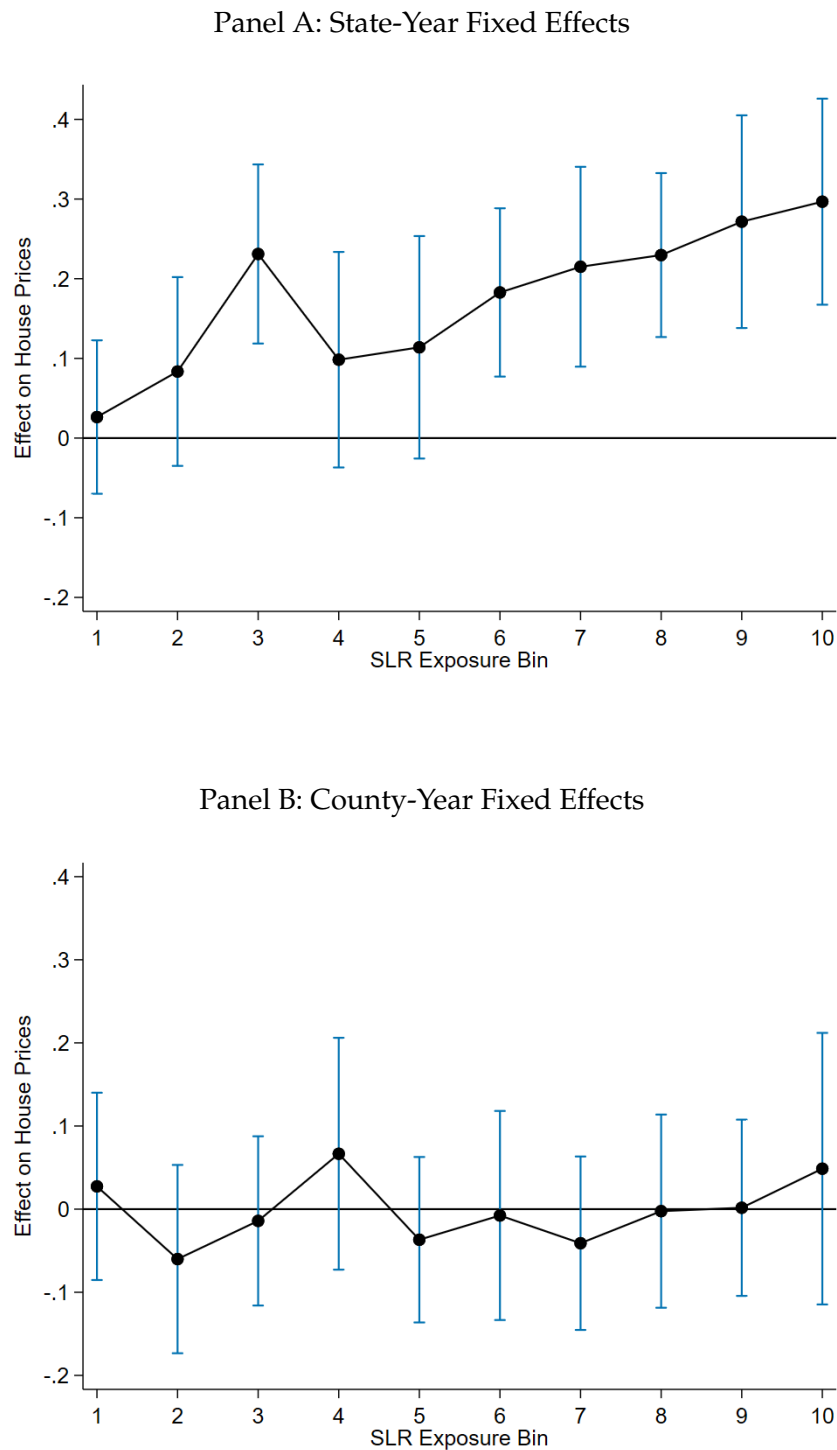


Panel B: Southeast and Gulf Coast



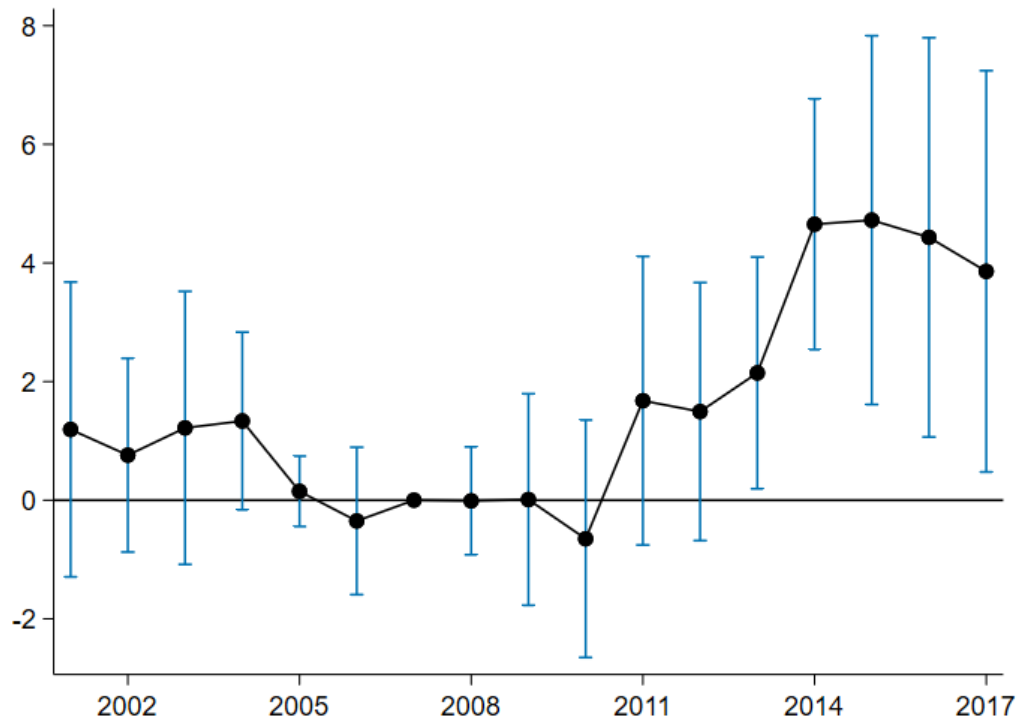
Note: This figure maps the fraction of properties in coastal school districts that is exposed to chronic tidal flooding after six feet of global average sea level rise. Gray areas represent districts that do not appear in the sample of municipal bonds described in Section 2. For ease of presentation,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

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



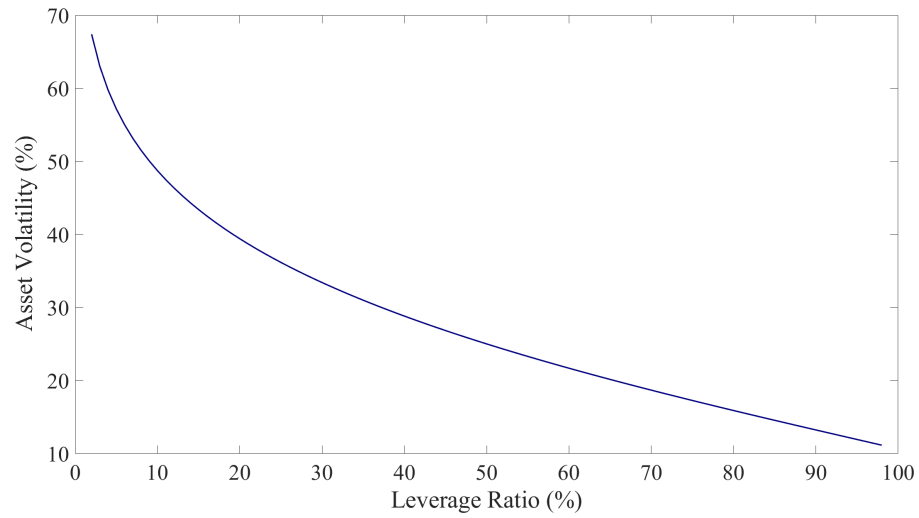
Note: This figures plots coefficients from semi-parametric regressions of log median house prices on SLR exposure. Geographic areas are sorted into decile bins based on SLR exposure for the area. Coefficients are estimated relative to areas with zero SLR exposure. Panel A measures exposure at the county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

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



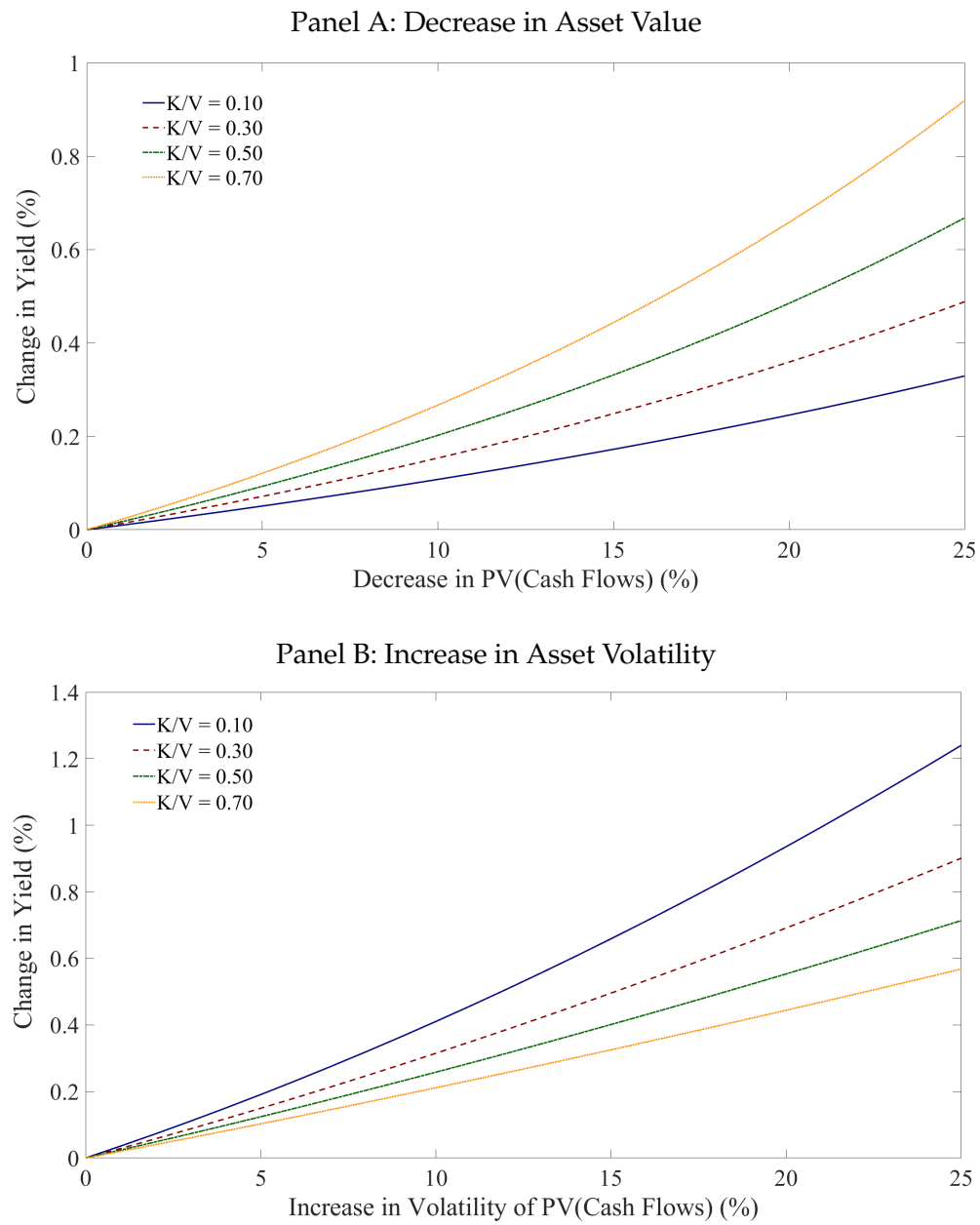
Note: This figure plots the annual effect of a one standard deviation increase in SLR exposure on municipal bond credit spreads. Spread is defined as the difference, in basis points, between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve. The coefficients come from the regression specified in equation (1), with yearly coefficients, and include county-year-month and district fixed effects and controls for liquidity, callability and the term structure of credit spreads. The baseline period is 2007. The SLR exposure measure is defined as the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to have zero mean and unit standard deviation. The vertical bars denote 95% confidence intervals based on standard errors are clustered by county and year-month.

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

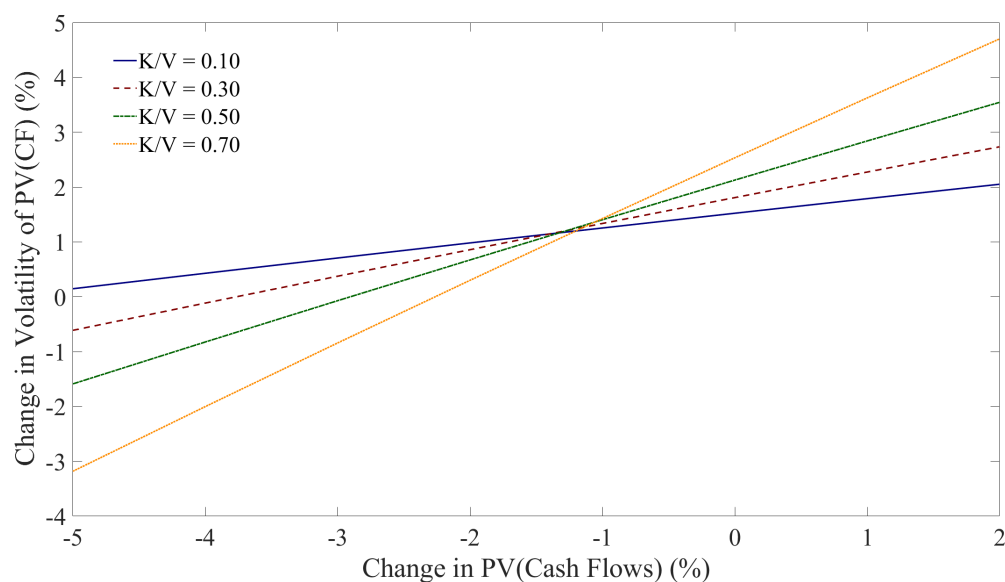


Note: This figure plots the model-implied volatility (σ) from equation (3) as a function of the leverage ratio (K/V). The other model parameters are: $y = 3.24\%$, $r = 2.68\%$, and $T = 7.5$.

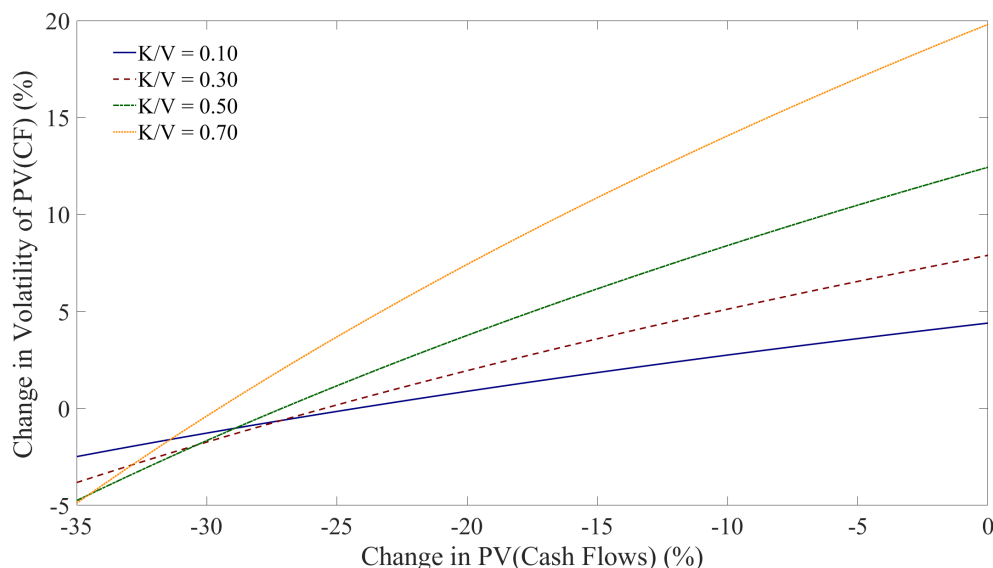
Figure 7: Effects of Asset Value and Volatility Shocks on Municipal Bond Yields



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 bps increase in yield. Panel D considers the combination of shocks that matches the 23.4 bps 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 $T = 22.5$.

Table 1: Summary Statistics

	(1)			(2)		
	<i>Full Coastal Sample</i>			<i>SLR Exposed Districts</i>		
	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.
SLR Exposure	0.03	0.09	185,983	0.07	0.13	83,587
Storm Surge Exposure	0.58	1.47	185,983	1.28	1.98	83,587
Yield-to-Maturity (%)	3.25	1.23	185,983	3.23	1.21	83,587
MMA AAA-Rated Tax-Exempt Rate (%)	2.70	1.29	185,983	2.66	1.27	83,587
Spread over MMA Curve (bps)	55.09	53.92	185,983	56.76	54.79	83,587
Time to Maturity	9.65	6.14	185,983	9.37	5.87	83,587
Bond Age	3.86	2.75	185,983	3.80	2.71	83,587
Monthly Trading Volume (\$000s)	593.66	2980.38	185,983	574.77	2865.31	83,587
Monthly Turnover	0.20	0.41	185,447	0.20	0.41	83,293
Monthly S.D. of Price (per \$100)	0.88	0.69	165,091	0.89	0.69	73,935
1(Callable)	0.61	0.49	185,983	0.61	0.49	83,587
1(Insured)	0.41	0.49	185,983	0.45	0.50	83,587
1(General Obligation)	1.00	0.07	185,983	0.99	0.07	83,587
Residents' Average Income (\$000s)	38.08	25.00	185,983	36.10	22.97	83,587
Median House Price (\$000s)	270.96	187.14	152,803	275.26	182.44	69,478
Property Tax Rate	0.02	0.00	185,983	0.02	0.00	83,587
School Local Funding	0.51	0.03	185,983	0.51	0.03	83,587

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.

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

	(1)	(2)	(3)
SLR Exposure	-1.270** (-2.06)		
SLR Exposure \times 1(Year 2001)	0.073 (0.06)	0.326 (0.37)	1.225 (0.91)
SLR Exposure \times 1(Year 2002)	0.493 (0.49)	0.468 (0.64)	1.096 (0.96)
SLR Exposure \times 1(Year 2003)	-0.140 (-0.18)	-0.210 (-0.23)	1.426 (1.09)
SLR Exposure \times 1(Year 2004)	-2.340** (-2.61)	-2.016* (-1.79)	1.409** (2.09)
SLR Exposure \times 1(Year 2005)	-0.665 (-1.27)	-0.397 (-0.74)	0.398 (1.20)
SLR Exposure \times 1(Year 2006)	-0.257 (-0.40)	-0.433 (-0.75)	-0.115 (-0.22)
SLR Exposure \times 1(Year 2008)	0.870 (1.02)	0.615 (0.84)	0.062 (0.15)
SLR Exposure \times 1(Year 2009)	1.912** (2.25)	1.284* (1.93)	0.554 (0.63)
SLR Exposure \times 1(Year 2010)	0.927 (0.70)	0.058 (0.04)	-0.064 (-0.07)
SLR Exposure \times 1(Year 2011)	2.373* (1.89)	1.350 (1.21)	1.874 (1.30)
SLR Exposure \times 1(Year 2012)	1.973 (0.94)	0.950 (0.44)	1.910 (1.63)
SLR Exposure \times 1(Year 2013)	2.982 (1.34)	1.864 (0.81)	2.288** (2.01)
SLR Exposure \times 1(Year 2014)	5.872* (1.91)	4.888 (1.42)	4.734*** (5.16)
SLR Exposure \times 1(Year 2015)	5.331* (1.84)	4.641 (1.40)	5.277*** (3.96)
SLR Exposure \times 1(Year 2016)	5.215* (1.97)	4.756* (1.74)	4.962*** (2.75)
SLR Exposure \times 1(Year 2017)	5.299** (2.26)	4.941** (2.20)	3.864** (2.24)
Controls	N	N	Y
Year-Month FE	Y	Y	Y
District FE	N	Y	Y
County-Year-Month FE	Y	Y	Y
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, with 2007 as the baseline period. 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. SLR Exposure is defined as the fraction of residential properties that would be inundated by six feet of sea level rise, 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 the year; 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 3: Effect of Sea Level Rise Exposure and Bond Spreads by Maturity

	(1)	(2)	(3)
SLR Exposure \times 1(Post)	2.929** (2.15)	2.744** (2.37)	
SLR Exposure \times 1(Post) \times Log(Maturity)			1.276** (2.33)
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
Observations	65,193	90,019	155,212

Note: This table reports estimates of equation (1), but with the yearly coefficients collapsed into pre-2013 and post-2012 periods. The dependent variable is the volume-weighted average credit spread of a municipal bond. Observations are at the bond-year-month level. Post is an indicator equal to one for observations occurring after 2012 and zero otherwise. SLR Exposure is defined as the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. Column (3) adds a triple interaction with the bond's remaining time to maturity in years and the post-2012 indicator. Controls include the logarithm of the bond's time to maturity, callability and insured status interacted with the year; 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. Column (1) restricts the sample to bonds with less than 10 years in maturity, while column (2) restricts the sample to long-maturity bonds. *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 Sea Level Rise Exposure versus Storm Surge Exposure

	(1)	(2)	(3)
SLR Exposure \times 1(Post)	3.551* (1.95)	6.973*** (3.28)	1.421 (0.86)
Storm Surge Exposure \times 1(Post)	-0.340 (-0.14)	-5.669 (-1.53)	1.985 (0.81)
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
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 adding an interaction between the post-2012 and our measure of storm surge exposure. The dependent variable is the volume-weighted average credit spread of a municipal bond. Observations are at the bond-year-month level. Post is an indicator equal to one for observations occurring after 2012 and zero otherwise. SLR Exposure is defined as the fraction of residential properties that would be inundated by six feet of sea level rise, 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 the year; 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. Column (1) restricts the sample to bonds with less than 10 years in maturity, while column (2) restricts the sample to long-maturity bonds. *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 Sea Level Rise Exposure and Bond Spreads by Tax Regime

	(1)	(2)	(3)	(4)
SLR Exposure \times 1(Post)	2.032 (1.66)	-2.639 (-0.98)	-0.761 (-1.08)	4.012*** (4.66)
SLR Exposure \times 1(Post) \times Property Tax Rate	1.167** (2.40)			
SLR Exposure \times 1(Post) \times School Local Funding		6.202** (2.46)		
Log(Median House Price)				-12.322*** (-2.70)
Sample	Full	Full	CA	Full
Controls	Y	Y	Y	Y
District FE	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y
Observations	155,212	155,212	128,626	127,208

Note: This table reports estimates of equation (1), with the yearly coefficients collapsed into pre-2013 and post-2012 periods, and adding an interaction with measures of school districts' reliance on property taxes. The dependent variable is the volume-weighted average credit spread of a municipal bond. Observations are at the bond-year-month level. 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. SLR Exposure is defined as the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. Post is an indicator equal to one for observations occurring after 2012 and zero otherwise. State Property Tax 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. Log(Median House Price) is the median transaction price each year for single family residences in the school district. Controls include the logarithm of the bond's time to maturity, callability and insured status interacted with the year; 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 Sea Level Rise Exposure and Bond Spreads by Local Beliefs

	(1)	(2)	(3)
SLR Exposure \times 1(Post)	5.629*** (5.91)	-1.144 (-0.53)	4.634*** (4.13)
SLR Exposure \times 1(Post) \times State Worry			3.421** (2.61)
Level of Concern	Worried	Not Worried	All
Controls	Y	Y	Y
District FE	Y	Y	Y
County-Year-Month FE	Y	Y	Y
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 adding an interaction with state residents' level of concern about global warming. The dependent variable is the volume-weighted average credit spread of a municipal bond. Observations are at the bond-year-month level. 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. SLR Exposure is defined as the fraction of residential properties that would be inundated by six feet of sea level rise, normalized to zero mean and unit standard deviation. Post is an indicator equal to one for observations occurring after 2012 and zero otherwise. State Worry is a standardized measure of global warming concerns from the Yale Climate Opinions map. Worried states include (in order of concern) New York, Massachusetts, New Jersey, Rhode Island, Connecticut, and Maine, while not worried states include Texas, North Carolina, South Carolina, Mississippi, and Louisiana. Controls include the logarithm of the bond's time to maturity, callability and insured status interacted with the year; 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: Model-Implied Changes in Credit Spreads due to Economic Shocks

T	7.5	7.5	7.5	22.5	22.5
y (%)	3.24	3.24	3.24	4.70	5.81
r (%)	2.68	2.68	2.68	4.00	4.00
α (%)	0	25	0	0	0
K_S/K (%)	0	0	50	0	0
K/V (%)	40	40	40	40	40
σ (%)	27.8	24.8	23.9	30.6	41.3
$\Delta V = -1\%$	0.015	0.018	0.019	0.007	0.012
$\Delta V = -5\%$	0.081	0.093	0.104	0.039	0.060
$\Delta V = -10\%$	0.174	0.203	0.230	0.083	0.125
$\Delta V = -20\%$	0.412	0.488	0.564	0.184	0.273
$\Delta \sigma = +1\%$	0.026	0.026	0.030	0.026	0.052
$\Delta \sigma = +5\%$	0.137	0.134	0.159	0.133	0.264
$\Delta \sigma = +10\%$	0.287	0.279	0.335	0.276	0.541
$\Delta \sigma = +20\%$	0.623	0.599	0.734	0.591	1.135

Note: This table reports estimates from alternative specifications of the structural model of credit risk described in Section 4.1. All specifications hold the leverage ratio (K/V) fixed at 40%, the average of the four ratios considered in Figure 7, and compute the implied asset volatility based on this and the other model parameters. The top panel of the table reports the parameters associated with the specification in each column, while the bottom panel reports the change in yield (in percentage terms) from proportional reductions in asset values and increases in volatility listed in the rows. The first three specifications are: the baseline model used in Figure 7, the baseline model with a proportional bankruptcy cost of 25%, and the baseline model with a debt structure of 50% senior loans and 50% junior bonds. The last two specifications are based on calibrating the model to the mean and 90th percentile credit spreads, respectively, of new issue municipal bonds with 25 years or more to maturity.