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Sea-Level Rise Exposure and Municipal Bond Yields

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Municipal bond markets began pricing sea-level rise (SLR) exposure risk in 2013, coinciding with upward revisions to worst-case SLR projections and accompanying uncertainty around these projections. The effect is larger for long-maturity bonds and not solely driven by near-term flood risk. We use a structural model of credit risk to quantify the implied economic impact and distinguish between the effects of underlying asset values and of uncertainty. The SLR exposure premium exhibits a trend different from house prices and is unaffected by house price controls. Together, our results highlight the importance of climate uncertainty in driving municipal bond prices. (*JEL* G1, Q54)

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Over the past two decades, popular interest in climate change has increased dramatically as scientific forecasts have become more dire. One consequence of a warming climate is sea-level rise (SLR). Since the Intergovernmental

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Panel on Climate Change (IPCC) report in 2007, improvements in scientific methods for forecasting SLR have led to larger and more variable projections, with current upper-bound projections of 2.5 meters (8.2 feet) by 2100 (e.g., Stocker et al. 2013; DeConto and Pollard 2016; Sweet et al. 2017; Garner et al. 2018). 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 these hazards, policymakers in the United States and abroad have begun to invest in relocation programs, raising questions about whether at-risk coastal communities should continue to be redeveloped. Estimating the economic impact of SLR exposure and when it will manifest is important for assessing the potential benefits of climate remediation, which can be weighed against the costs of interventions.

In this paper, we examine how exposure to SLR risk is priced in the municipal bond market and quantify the real economic impact implied by the pricing of SLR risk. Municipal bonds provide a useful setting for assessing investors' expectations of the local impact of climate risk because the sources of repayment are tied to local economic conditions. This is especially so for the school district bonds that compose our sample, which are commonly backed by local real estate taxes. Since the prices of municipal bonds reflect the likelihood that local government cash flows will be sufficient to make debt payments, this market provides an opportunity to translate effects on asset prices into more general economic effects of SLR exposure on coastal communities.

However, estimating the effect of SLR exposure on the value of municipal bonds and their underlying cash flows is challenging for two reasons. The first challenge is an econometric one: factors correlated with SLR exposure (e.g., proximity to the coast, current flood risks) are also correlated with time-invariant and time-varying economic risks. Solving this issue requires an empirical approach such that these factors can be held fixed while varying SLR risk. Our approach uses detailed local variation in school districts' SLR exposure to compare bonds from issuers in the same U.S. county that trade in the same time period, but vary in their exposure to SLR risk, while holding fixed things like current flood risk. The second challenge is theoretical: how 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 and using it to distinguish the effects of SLR risk on underlying asset values and uncertainty.

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 worst-case scientific SLR projections as well as uncertainty in these SLR projections and popular interest in SLR. We estimate that a one-standard-deviation (approximately 10 percentage points) increase in the fraction of properties exposed to six feet of sea-level rise is accompanied by a 5.3-basis-point (bp) increase in municipal bond credit spreads in 2015, equivalent to 9% of the average spread in our sample. The 95% confidence interval associated with this estimate can rule out effects smaller than 2.7 bp or larger than 7.9 bp, and the estimates from 2014 to 2017 all fall within these bounds. This effect is similar in magnitude to the difference in municipal bond yields between states that allow municipal bankruptcy relative to states that do not (Gao, Lee, and Murphy 2019).

To the extent that climate change is a salient risk to bondholders, the effect should be largest in longer-maturity bonds. This is true regardless of the precise nature of the risk (e.g., migration due to expected inundation, worsening storm intensity). Consistent with this, the within-district effect of SLR on credit spreads is significantly larger for long-maturity bonds. However, at the district level, long-run SLR exposure is also highly correlated with storm surge risk. If SLR exposure proxies for hurricane risk, then our results are also consistent with investors pricing a near-term increase in storm frequency and intensity instead of exposure to long-run sea-level rise and inundation. Controlling for storm surge risk helps to disentangle these explanations. We find that the credit spread premium after 2012 is primarily attributable to SLR exposure, and not our measure of storm surge risk.

To interpret the economic magnitude of our findings, we adapt the Merton (1974) model of credit risk to the municipal bond market. We use the model to translate the estimated effects of SLR exposure on bond yields into implied changes in the future distribution of local government cash flows. After calibrating the model to match the average yield of municipal bonds in our sample, we find that the estimated 5.3 bp SLR exposure premium (and the confidence interval surrounding it) is consistent with a reduction of 2.4% to 5.6% (1.3% to 8.1%) in the present value of the underlying cash flow stream, a proportional increase of 1.6% to 2.9% (0.8% to 4.2%) in the volatility of cash flows, or some combination of these effects, depending on the issuer's financial leverage. We consider a wide range of leverage ratios in the calibration to ensure our inability to observe issuer leverage ratios does not affect our conclusions. The estimated effects of SLR exposure on bond yields do not imply the expectation of catastrophic losses from climate-induced default in the municipal bond market, but they do suggest that investors anticipate a material economic impact of SLR risk on exposed municipalities. Moreover, the model implies two distinct channels through which SLR could affect municipal debt pricing: either the present value of municipal cash flows or the riskiness of the cash flows.

To assess the relative importance of these two channels, we incorporate two additional sources of data: data on house prices as a proxy for underlying asset values, and data on scientific uncertainty about SLR forecasts to construct proxies for uncertainty about SLR's future impact on municipal cash flows. First, we find that including house prices as flexible controls does not change our main regression estimate, despite house prices correlating with municipal credit spreads in an intuitive way and SLR predicting lower average house prices toward the end of our sample (consistent with Bernstein, Gustafson, and Lewis 2019; Baldauf, Garlappi, and Yannelis 2020). Assuming house prices are a good control for the present value of municipal cash flows, this suggests that the impact of SLR exposure on asset values is not the primary driver of municipal bond yields during this sample, though we cannot rule out that it has some effect.[1]

Rather, our body of evidence suggests that uncertainty about future municipal cash flows is the most likely driver of the SLR exposure premium. Further bolstering this interpretation, we show that dispersion in scientific projections of SLR is a stronger predictor of increases in the SLR premium than the median projection over the sample period.[2] Much of the previous work has emphasized the role of SLR exposure in changing contemporaneous asset prices (such as house prices), while being agnostic on the mechanism. Our results suggest that holding fixed the current discounted value of the assets, the heightened level of uncertainty has increased yields on municipal bonds (consistent with work by Barnett, Brock, and Hansen 2020, Kruttli, Roth Tran, and Watugala 2021).

In a set of auxiliary tests, we explore how state-level differences in local taxation, concern about climate change, and support for distressed municipalities influence the estimated SLR exposure premium. Intuitively, the SLR exposure premium is larger for bonds whose school districts rely more on local property taxes for budgetary needs and smaller for bonds whose districts rely more on state-level funding. We also find that the premium is larger in states where residents report higher levels of concern about climate change. This finding is consistent with existing literature showing that an area's beliefs about climate change affect how SLR exposure is priced in real estate markets (e.g., Bernstein, Gustafson, and Lewis 2019; Baldauf, Garlappi, and Yannelis (2020)). Finally, we show that our estimates are not driven by state-level policies on municipal distress (Gao, Lee, and Murphy (2019)); in fact, the estimated SLR premium would likely be larger in the absence of state support for distressed municipalities. Taken together, these findings suggest a role for statewide risk-sharing to support areas exposed to climate change, especially in states where residents are concerned about this risk.

This paper contributes to the emerging literature on the financial implications of climate risk. Environmental risks have been linked to the valuation

[1] This also casts doubt on explanations that current costs from SLR exposure (e.g., flood insurance) are driving municipal bond yields, since these costs would also change contemporaneous house prices.

[2] We cannot rule out that rising attention to climate risk also plays a role in the price effects we observe. For survey evidence on household attention, see Funk and Kennedy (2020).

of firms (e.g., Bansal, Kiku, and Ochoa 2016; Berkman, Jona, and Soderstrom 2021; Hong, Li, and Xu 2019; Kruttli, Roth Tran, and Watugala 2021) and their cost of capital (e.g., Sharfman and Fernando 2008; Chava 2014; Delis, de Greiff, and Ongena 2021), as well as their operating performance (e.g., Barrot and Sauvagnat 2016; Addoum, Ng, and Ortiz Bobea 2020) and financial policies (e.g., Dessaint and Matray 2017). With respect to capital supply, research has shown that climate risk affects the allocation of credit by banks (e.g., Cortés and Strahan 2017; Brown, Gustafson, and Ivanov 2021) and the beliefs of institutional investors (Krueger, Sautner, and Starks 2020). Baker et al. 2018, Flammer 2021, and Larcker and Watts 2020 study the pricing of "green" bonds issued to fund environmentally friendly projects. Giglio, Maggiori, and Stroebel (2014) and Giglio et al. (2021) show that low discount rates should be used to discount the long-run risks of climate change. We contribute to this body of work by showing that the cost of debt financing depends on location-specific exposure to climate risk. This dependence is growing over time and implies that climate risk is expected to incur real economic costs on exposed issuers at both short and long horizons.

Our findings build on prior work, including Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020), that shows a negative effect of SLR exposure on residential real estate prices. These studies identify the effect of SLR exposure by comparing observably similar properties in close proximity to each other, so they do not address the question of how SLR risk affects the broader economy in coastal areas. Our evidence suggests that uncertainty about SLR's future impact and associated downside risks, rather than reductions in asset values, is affecting local economies today.[3] Our evidence on the importance of uncertainty in SLR projections supports the arguments in Hansen (2022) and Ilhan, Sautner, and Vilkov (2021) on the policy challenges presented by the highly uncertain nature of climate risks. Our findings also build on theoretical work by Barnett, Brock, and Hansen (2020), in which the "risk" and "ambiguity" components of uncertainty both relate to our empirical measurement of scientific uncertainty in SLR forecasts. The extent to which uncertainty about future climate risk propagates into current price movements is a novel empirical finding in the climate finance literature, highlighting a benefit of studying the value of debt claims like municipal bonds, which have option-like payoffs that depend on downside risk in local economies, rather than the value of underlying assets, such as houses, which are exposed to both downside risk and upside potential.

Another contribution of this paper is to adapt a structural model of credit risk from the corporate finance literature to the municipal bond market. The model

[3] Another distinguishing factor is that the pricing of real estate may be affected by the risk aversion of buyers who account for idiosyncratic risks when valuing an asset that accounts for a large fraction of their wealth. Our examination of municipal bonds sheds light on the expected economic impact of SLR exposure as perceived by financial market participants who can diversify away from location-specific flood risk.

highlights the joint roles of asset values and cash flow volatility in affecting bond prices and allows us to quantify the economic impact implied by our bond pricing estimates. Our calibration approach is straightforward to apply in other nonstandard settings where it may be difficult to observe the issuer's capital structure and the market value of its assets. We argue that theoretical models are a valuable source of discipline in the interpretation of reduced-form estimates, especially in settings where the underlying shock is difficult to quantify in dollar terms.[4]

This structured approach to interpreting the evidence, along with our novel evidence on the uncertainty channel and the use of reduced-form empirical methods that account for time-varying county-level economic conditions, all differentiate our work from Painter (2020), who studies a similar research question using data on new bond issues and a different measure of flood risk. Our study, however, is better able to address the challenge posed by Dell, Jones, and Olken (2014) to use present day events and information to construct a convincing case for the effects of long-run climate change risks. The first important difference between our findings and those in Painter (2020) is with respect to magnitude. Painter (2020) estimates a 23.4-bp increase in long-maturity bond yields in response to a one percent increase in flood risk, measured by Hallegatte et al. (2013) as the annual gross domestic product (GDP) loss due to 40 centimeters (1.3 feet) of sea-level rise.[5] Our structural model suggests that this estimate implies substantially more economic damage than implied by Hallegatte et al. (2013), on the order of a 25% reduction in the present value of the cash flows backing bond repayment.

The timing of our estimated effects also differs from Painter (2020). We find an insignificant effect of SLR exposure on municipal bond spreads through 2012 and a positive effect afterward. 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 Internet Appendix Section A5, 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. Together, the differences between our

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

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

work and Painter (2020) help establish a link between long-run climate risks and municipal bond yields, which was previously not separable from current flood risks.

From a policy standpoint, the implications of our estimates are materially different from those in Painter (2020). Our results suggest that interventions to remediate SLR risk can create value for investors and lower borrowing costs for municipalities today, and that these efforts would lead to meaningful economic benefits for exposed communities in both the near and long terms. Most notably, however, our results suggest that general uncertainty about SLR is an important driver of increased yields. Improvements in SLR forecasting may thus have consequences for financial markets: On one hand, improvements may lead to reduced uncertainty as better data, measurement, and modeling improve the precision of estimates. On the other hand, new techniques may lead to greater uncertainty, similar to the increase in uncertainty due to the change in SLR modeling techniques in the 2010s. In either case, residual uncertainty about climate risk will likely remain an important concern for policymakers even as more efficient reflections of the true climate risk and ambiguity emerge.

1. Background on Sea-Level Rise and Municipal Bonds

Sea-level rise exposure is a geographic phenomenon, with coastal areas at the highest risk. Whether this exposure translates into inundation and creates a material threat to U.S. coastal communities depends on the realized level of future global SLR, a hotly debated question among policymakers and politicians. While it is widely recognized the oceans rose by 1–2 millimeters per year in the 20th century, disagreement and uncertainty arise when translating these past trends into future projections and when mapping sea-level rise into economic damages. We discuss the scientific background on sea-level rise projections and the challenges of mapping this to economic consequences below.

1.1 The evolution of sea-level rise projections

Scientific studies projecting global sea-level rise have existed since the 1980s but have proliferated since the end of the 2000s. The IPCC has issued periodic reports on climate change, synthesizing and forecasting beliefs about future sea-level rise, and in 2007, their report concluded that seas were likely to rise by between 0.18 and 0.59 meters by 2100. These projections were similar to the conclusions reached by Church and White (2006) when extrapolating the current rate of SLR acceleration through the year 2100, but lower than estimates from the IPCC's last report in 2001 and prior periods (Garner et al. 2018).

Following this 2007 report, there was substantial disagreement in the scientific community surrounding the 2007 estimates, which led to an influx of studies attempting to more accurately project sea-level rise.[6] One important part of the scientific disagreement stemmed from differences in how to model the factors contributing to SLR. For example, many scientists believed that the 2007 projections were too low because they did not account for contributions from Greenland glaciers and West Antarctic ice streams Meehl et al. (2007), among other factors. Rahmstorf (2007) and others began to replace models that attempt to fully predict the climate (physical climate models) with statistical models of key outcomes (semiempirical strategies). This new approach substantially increased the range of year 2100 SLR projections; between 2007 and 2013, the range of projections from semiempirical models was 0.17 to 2.05 meters (Garner et al. (2018)). Notably, some scientists continue to predict negligible SLR this century (e.g., Hansen, Aagaard, and Kuijpers 2015).

Another important aspect of the disagreement comes from differences in views on the long-term path of global carbon emissions. These paths have become standardized in the scientific literature following the 2012 IPCC report with the development of representative concentration pathways (RCP) scenarios (Van Vuuren et al. 2011), which the climate modeling community now frequently uses for long-term and near-term modeling experiments. The pathways take on four levels—RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5—all of which relate to greenhouse gas concentration and in turn predicted temperature. RCP 8.5 reflects a high emissions scenario, representing what could be reasonably expected to happen if current high emissions trends persist without mitigation. The other RCP scenarios reflect mitigation efforts that stabilize greenhouse concentrations below certain levels.[7] Views on these different scenarios can also drive differences in expected SLR, even if the underlying model for each given scenario were identical.

In Figure 1, we use information provided in the Garner et al. (2018) survey to quantify the evolution of SLR projections, both in terms of the *level* of predicted sea-level rise and in terms of the uncertainty surrounding these estimates. This uncertainty around the estimates reflects *researchers*' level of confidence in their projections, and not just the variation across different studies. We present both the level and uncertainty across three RCP scenarios: high emissions (8.5), reduced emissions (4.5), and low emissions (2.6).[8] To provide the broadest possible picture, we use all studies in the survey, but are limited by the fact that emission categories were not uniform until 2012. In Internet Appendix

[6] There were no scientific studies projecting future global SLR between the 2001 and 2007 IPCC reports (Garner et al. 2018), leading to a gap in scientific projections from 2001 to 2007.

[7] Prior to this standardization, the Special Reports on Emissions Scenarios (SRES) were used, but those explicitly account for carbon emissions controls and were therefore not as uniformly applied across the scientific community.

[8] Aggregation of these three scenarios depends on one's beliefs over the different scenarios. Panel A of Figure 1 presents the simple average across these scenarios; we present an alternative way to aggregate these beliefs in panel C by identifying the relative prominence of different scenarios in the academic literature. We use this measure to aggregate across high and reduced emissions in Section 4.2.2.

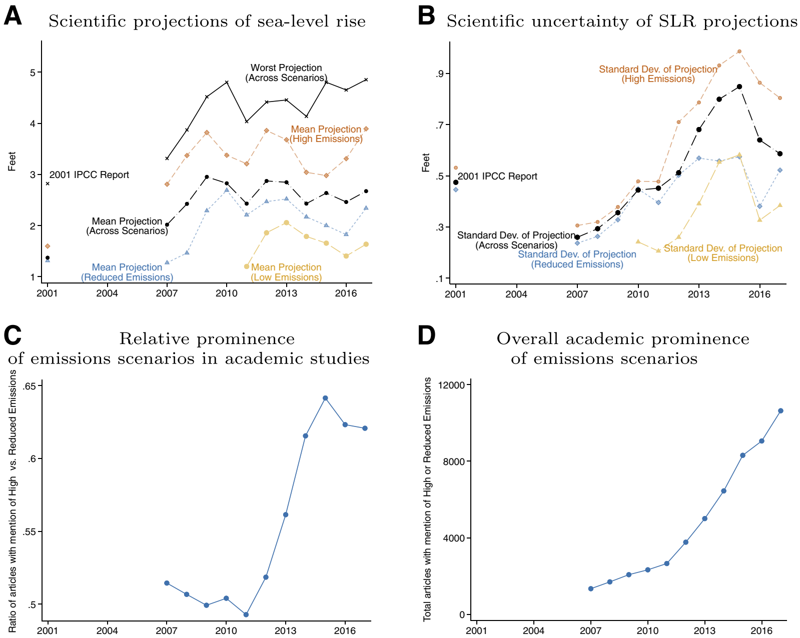

Figure 1
Time series of sea-level rise projections and climate scenarios
This figure plots the different summary statistics of studies surveyed in Garner et al. (2018). Panels A and B plot the annual values for mean (dashed line in panel A), worst-case (solid line in panel A). All measures are computed by first calculating the statistic for each study and then averaging across all studies in the rolling 2-year window. Mean (Standard deviation) is computed by taking the average 2100 SLR estimate (standard deviation for 2100 SLR estimate) for every scenario considered in a study, then averaging these within-scenario means (standard deviations) across all scenarios considered in the study, and finally averaging across all studies in the rolling 2-year window. Worst is the maximum upper-bound estimate across all scenarios used in a study, averaged across all studies in a 2-year rolling window. We omit measures between 2001 and 2007 because there were no new projections of global SLR between 2002 and 2006. Panel C plots the ratio of total obtained from Google Scholar of the number of studies which discuss high forecast models (RCP8.5 or SRES A) divided by the total number of studies which cite medium or high scenarios (e.g., RCP 8.5, RCP 4.5, SRES A, and SRES B). Panel D plots the total combined counts of the results of the two searches.

Section A1 and Internet Appendix Figure A1, we replicate Figure 1 using the subset of studies from Garner et al. (2018) that are most comparable across time. Figure 1 plots the time series of three measures of 2100 SLR projections across different scenarios, each of which are 2-year averages that equal-weight each study in the Garner et al. (2018) survey. The three measures we estimate are

1. *Mean* by computing the average 2100 SLR estimate for every scenario considered in a study, then averaging these within-scenario means across scenarios. These reflect the *level* prediction of SLR.
2. *Worst* as the maximum upper-bound estimate across all scenarios used in a study.

3. *Standard deviation* by taking the standard deviation of estimated 2100 SLR for each scenario considered in a study, then averaging these within-scenario standard deviations across all studies that consider the scenario.

Panel A of Figure 1 plots the evolution of *Mean* and *Worst* over our sample period, which reflect views on the expected level for the three scenarios as well as the worst forecast projection of SLR in 2100.[9] The projected means across scenarios rise from 2007 to 2009, and then stays relatively flat for the remainder of our sample. There is a larger and longer increase in the worst-case projections, which rise by about 65% from around 3 to 5 feet between 2007 and 2010. This timing corresponds to the influx of semiempirical studies and the adoption of RCP scenarios. These worst-case projections stabilize between 4 and 5 feet through the end of our sample in 2017. While there is a significant increase across all scenarios and measures by 2010 relative to the 2007 and 2001 IPCC reports, the projections afterward change little.

Panel B of Figure 1 plots *Standard deviation* over our sample period for the three scenarios. *Standard deviation*, which measures typical within-scenario uncertainty, more than triples between 2007 and 2015 for the status quo scenario and then declines from 2015 to 2017. The standard deviation also nearly doubles for the reduced and low emissions scenarios as well, suggesting increased uncertainty despite relatively flat level projections. This contrast of relatively flat mean projections but rising scientific uncertainty (both in worst-case projections and standard deviations of projections), which Garner et al. (2018) discuss in their abstract, is less widely known by nonclimate scientists, but reflects an important feature of current projections, the feature being that the level prediction has not changed tremendously, but the range of outcomes has continued to grow, implying significant downside risk.

One limitation of the scientific literature is that it cannot identify which emissions scenario will manifest, primarily because the future path is determined by ongoing and future emissions decisions. Nevertheless, the path of emissions is critical to projecting year 2100 SLR. In panel C of Figure 1, we more explicitly model attention to SLR academic literature. Specifically, we measure the total number of papers that reference high emissions scenario and medium emissions scenario by searching Google Scholar for the terms "RCP 8.5 climate" or "SRES A1 climate" and "RCP 4.5 climate" or "SRES B1 climate" respectively.[10] We construct a measure that is the ratio of total results using the high emissions scenario divided by the total results using high emission scenario plus the total results using the medium emissions scenario.

[9] There is only one low emission case pre-2011, in 2007, and so we omit it to for presentation purposes.

[10] Prior to the 2012 IPCC report, high emissions scenarios were classified as SRES A1, while medium emissions fell under SRES B1. After the IPCC report, SRES was largely phased out and replaced by the more commonly known RCP scenarios.

(Note: For brevity, we will refer to high emissions as RCP 8.5 and medium emissions as RCP 4.5.) Our measure mimics a revealed preference approach: if scholars are more focused on higher emissions scenarios, it means that they think the insights around those scenarios are more useful than the lower emissions scenarios.

Panel C of Figure 1 shows that the relative amount of attention paid to the most extreme scenario, RCP 8.5, has increased over the past decade. Between 2007 and 2011 this ratio was approximately 0.5, suggesting there were twice as many references to the RCP 4.5 scenario. Between 2014 and the end of our sample this ratio was over 0.6. More generally, this increased interest in more dire scenarios reflects a growth in overall discussion of various emissions scenarios, as reflected in panel D of Figure 1.

1.2 Risks to municipal bond investors

Municipal bond investors care about how SLR affects the cash flows of their investment. The payoff structure of municipal bond investments suggests that investors will primarily care about how expected SLR projections or the uncertainty around those projections generates downside risk for coastal communities. Several layers of uncertainty are at play when factoring SLR exposure into municipal bond pricing. The first is that scientists do not know for certain how much temperatures will rise in the coming decades or how a given temperature rise will affect sea levels. This type of uncertainty is what the studies surveyed in Garner et al. (2018) grapple with directly.

Barnett, Brock, and Hansen (2021) also point out uncertainty in the economic damage function. In the context of SLR and municipal bond investors this is uncertainty about how a given amount of SLR affects municipal bond payouts. This damage function is quite complex since SLR exposure creates multiple types of short- and long-run risks for exposed areas.

In the long run, SLR may inundate coastal properties, a major risk for the health of coastal economies. In the near term, the warming climate has increased the projected severity of tropical storms and hurricanes. For instance, the fourth National Climate Assessment remarks that "the frequency, depth, and extent of tidal flooding are expected to continue to increase in the future, as is the more severe flooding associated with coastal storms, such as hurricanes and nor'easters" (Hayhoe et al. (2018), pp. 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 the effect of SLR on municipal bond prices 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. Recent evidence not only suggests that local property prices have begun to reflect the long-run risks associated with SLR exposure (e.g., Bernstein, Gustafson, and Lewis (2019); Baldauf, Garlappi, and Yannelis (2020)) but also downside risk to local economic activity more generally.

Consistent with anticipatory behavior on the part of local communities and exposed individuals, a growing body of anecdotal evidence shows that economic activity is moving away from SLR exposed areas in advance of flooding that is predicted to worsen over the coming decades. For example, Indonesia, the world's fourth most-populous country, plans to spend $33 billion to move its capital from Jakarta to the less-exposed island of Borneo.[11] In the United States, 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.[12] 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 in the downside risk reflected in scientific SLR projections. Empirically, we test this prediction against the null hypothesis that SLR exposure does not significantly affect municipal bond prices.

Our main empirical prediction is agnostic as to what type of inundation risk affects municipal bond yields and through what channels. The forward-looking nature of bond investors and the potential for economic damages to precede inundation raises the possibility that bonds of all maturities will be affected. However, we expect longer maturity bonds to be more affected because both short- and long-run risks are expected to increase as global temperatures rise over the coming decades. If investors are concerned about more severe storms, then measures of short-term flood risk should have more predictive power. If instead they are concerned about long-run inundation by rising oceans, then measures of long-run SLR exposure should matter more. We distinguish these risks empirically by including measures of SLR and storm surge exposure in the same regression and comparing the coefficient estimates across the maturity spectrum.

We also investigate the extent to which our main empirical prediction relates to existing evidence that SLR affects house prices (e.g.,

11 See Brito (2019).

12 See Flavelle (2020, 2021).

Bernstein, Gustafson, and Lewis 2019; Baldauf, Garlappi, and Yannelis 2020). Property taxes are an important source of repayment for municipal bonds, but since only a small percentage of properties in a given school district are exposed to significant SLR risk, existing evidence says little about whether SLR has a substantial impact on the total valuation of real estate when aggregated to the school district level. If any observed relation between SLR exposure and municipal bonds is due to investors' beliefs regarding expected SLR, then the relation will likely be subsumed by sufficient controls for contemporaneous house price movements. On the other hand, if uncertainty or downside risk in SLR projections drive a relation between SLR exposure and municipal bond yields, then the relation is more likely to persist even after accounting for any effect of SLR exposure on property values, as municipal debt is a contingent claim on the stream of tax revenues emanating from these values. Moreover, if downside risk or uncertainty about the future impacts of SLR is the key channel, as opposed to SLR's impact on current asset values, then we expect the positive relation between SLR exposure and municipal yield spreads to more closely track worst-case or uncertainty in scientific SLR projections compared to the median level of SLR projections. In Section 4 we dive more deeply into how to interpret the overall estimates of the SLR exposure premium using a model-based approach that incorporates both the asset value and uncertainty channels.

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

2. Data

Our empirical analysis studies the effect of SLR exposure on school district bond credit spreads. We focus on bonds issued by school districts for three reasons. First, public education is a common 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 United States comes from taxes on local real estate, so there is a direct link between school districts' ability to repay debts and the anticipated effects of SLR on local economies. Third, school districts compose the smallest, most clearly defined geographic areas among the various types of municipalities. This allows us to measure SLR exposure precisely and identify the effect on credit spreads, while controlling for time-varying local economic conditions at the county level. We explain why this level of granularity is critical to our identification strategy in Section 3.1.

Municipal bond yields are drawn from the intersection of the Mergent Municipal Bond Terms and Conditions database and historical transaction price data from the Municipal Securities Rulemaking Board (MSRB). We select school district bonds from these data by screening on primary and secondary education as the use of proceeds. Following past literature (Schwert 2017), we restrict attention to fixed-coupon tax-exempt bonds that trade at least 10 times, to ensure uniformity and a minimum level of liquidity. We exclude trades after a bond's advance refunding date, if applicable, because the bond is risk-free after that point (Chalmers 1998). Additionally, we exclude the first three months after issuance and the last year before maturity because these are times when transaction yields are especially noisy (Green, Hollifield, and Schurhoff 2007).[13] We do not impose any restriction on the type of bond issued, as the vast majority of school districts issue general obligation bonds.

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

We restrict the sample to coastal watershed counties, as defined by the National Oceanic and Atmospheric Administration (NOAA), in states with an ocean shoreline.[14] Our process to determine the SLR exposure for each school district bond issuer in coastal counties closely follows Bernstein, Gustafson, and Lewis (2019). First, we identify the location of each residential dwelling in the school district using the real estate assessor and transaction files in the Zillow Transaction and Assessment Dataset (ZTRAX). We then determine each property's SLR exposure using the NOAA SLR viewer (Marcy et al. 2011). Importantly, the NOAA's calculations account for tidal variation and other geographic factors that affect global oceanic volume increases on local SLR.[15]

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

14 See https://coast.noaa.gov/htdata/SocioEconomic/NOAA_CoastalCountyDefinitions.pdf.

15 Murfin and Spiegel (2020) argue that this exposure measure does not account for subsidence, so it does not accurately capture SLR risk. NOAA acknowledges this in the SLR methodology: "[subsidence] effects are still sufficiently unknown that they may compound or offset each other in unpredictable ways, such that including only some processes may cause greater error than ignoring them" (https://coast.noaa.gov/data/digitalcoast/pdf/slr-faq.pdf). In other words, the NOAA measure is based on more predictable and better understood factors, but may miss some less predictable aspects of SLR exposure. The relative sea-level rise (RSLR) measure proposed by Murfin and Spiegel (2020) could capture missing factors and represent SLR risk more accurately. Alternatively, it could introduce noise, as suggested by the NOAA, and may not represent investors' information sets because it is not easily accessible through public means. To address this issue, we construct a measure of RSLR exposure and present quantitatively similar bond pricing results in Internet Appendix Table A2 and Figure A2. The similarity is due to the high correlation between RSLR and SLR exposure at the district level (ρ=0.97), despite an imperfect correlation between RSLR and SLR at the

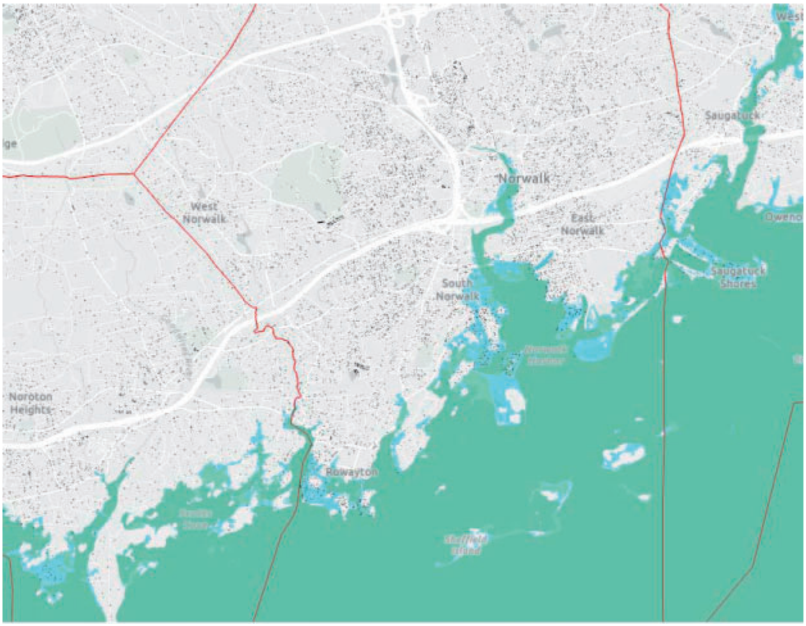


Figure 2
Sea-level rise exposure in Fairfield County, Connecticut
This figure maps housing locations and exposure to sea-level rise for a portion of Fairfield County, Connecticut. Black dots represent residential dwelling units; the green area represents the three-foot NOAA SLR scenario; the light blue area represents the six-foot scenario; and the red lines delineate school districts.

Figure 2 illustrates our methodology for a portion of Fairfield County in Connecticut. The black dots denote individual residential properties. The green area represents the extent of chronic tidal flooding after three feet of global average sea-level rise as predicted by NOAA SLR viewer, while the light blue area represents the exposure to six feet of SLR. Naturally, the region with six-foot exposure is larger and encompasses the three-foot exposure region. Finally, the red lines delineate school district boundaries.

To calculate our measure of SLR exposure at the school district level, we identify the number of properties exposed within each bucket of NOAA SLR risk and divide this by the total number of properties in the school district. For example, to calculate the district-level exposure to six feet of SLR, we count all dots within the blue and green areas and divide by the total number of dots in a district to obtain the fraction of exposed properties. We use the state and name of each school district to link the geographic exposure information to municipal

house level ($\rho = 0.77$). We observe a small decrease in the coefficient estimate, consistent with RSLR introducing measurement error and attenuation bias, but the difference is statistically insignificant.

bond issuers.[16] 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.[17]

Finally, given that the link between local property values and the cash flows supporting repayment of school bonds is central to our predictions, we exclude California from our main sample and analyze it separately because its school districts are insulated from this economic mechanism. Specifically, the impact of SLR on the creditworthiness of California school districts is dampened by Proposition 13, which caps property tax rates as a percentage of assessed value and the rate of assessment changes.[18] 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.[19]

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 Column 1 of Internet Appendix Table A5 using weighted regressions in which each state is equally represented.

16 The name matching proceeds in multiple steps. First, we clean and standardize the format of state names and common abbreviations. We then accept all exact matches between district and issuer names. For the remaining issuers, we remove stop words (e.g., "vocational," "technical," and "elementary") and repeat the matching using the shortened names. We match remaining issuers by hand when we deem the names a close enough match and exclude observations we cannot match.

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

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

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

Table 1
Summary statistics

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

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

Table 1 summarizes the variables used in our main analysis. About 46% of our observations are from districts that would experience at least some chronic inundation after six feet of global average SLR. On average, 7% of properties are exposed at the six-foot level in these districts. The average municipal bond-month observation in our sample has a yield of 3.24%, which is 57 bp over the AAA-rated benchmark curve. It has 10 years to maturity, has aged 4 years since issuance, and has $543,000 of monthly trading volume (conditional on nonzero trade). We find little unconditional difference in these characteristics between the exposed and full sample. After winsorizing at the 1% level, municipal bond credit spreads range from -19 bp to 261 bp relative to the MMA benchmark. The dispersion in spreads is narrow relative to other credit markets (e.g., corporate bonds) because of the low historical default rate in the municipal bond market.

3. Effect of SLR Exposure on Municipal Bond Yields

3.1 Identification strategy

Our central hypothesis is that SLR exposure has a positive effect on credit spreads that is increasing along with the rising scientific projections and uncertainty in these projections of SLR over our sample period. An important consideration when interpreting our results is that our empirical proxy for an area's SLR exposure is based on the percentage of properties in a school district that are exposed to six feet of SLR. We are agnostic regarding the extent to which investors, who are often retail investors in the municipal bond market, actually compute this exact measure of SLR exposure. We view our measure as representative of other SLR exposure measures, whether they are computed formally or informally. If our measure is not representative of the measures used by municipal bond investors, then the estimated relation between our proxy for a district's SLR exposure and municipal yield spreads will attenuate toward zero.

For our primary analysis, we estimate the following regression:

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

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, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020), we use six-foot SLR exposure as our primary measure of SLR risk. By the end of our sample period, most high-emissions scenarios project a 99th percentile of SLR exceeding six feet by the end of the century. Figure 3 displays the aggregated exposure measure for each school district in the municipal bond sample. SLR exposure is highly skewed, even in our sample, which is restricted to coastal counties. Most school districts in our sample do not have any SLR exposed properties. The 75th, 90th, and 95th percentiles of exposure to six feet of SLR are approximately 1%, 10%, and 20%, respectively.

We mitigate the possibility that SLR exposure relates to unobserved aspects of the area's economy in two ways. First, we include county-year-month fixed effects so that we identify the effect of SLR exposure on yields by comparing bonds issued by school districts located in the same county and traded in the same month. Under the sample restrictions described above, the mean (median) number of districts with bonds trading in a county-year-month is 3.6 (2).

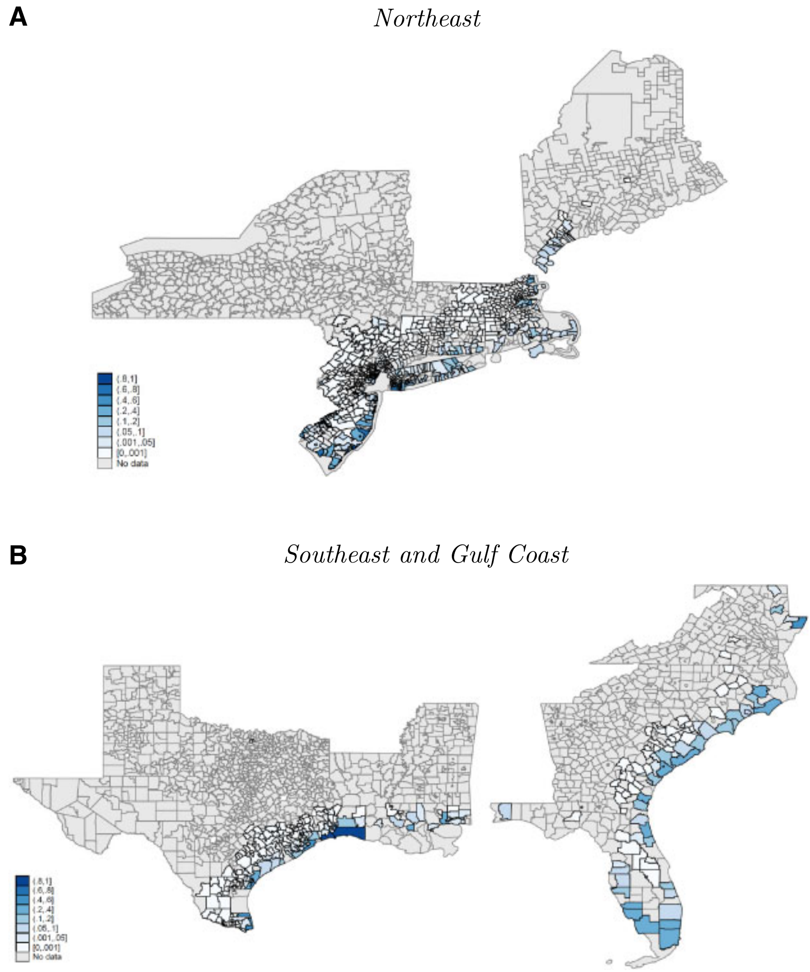


Figure 3
School district exposure to six feet of global average sea-level rise
This figure maps the fraction of properties in each coastal school district that is exposed to chronic tidal flooding after six feet of global average sea-level rise. Gray areas represent districts that do not appear in the sample of municipal bonds described in Section 2. For ease of presentation, we break the states into regions, with panel A focusing on the Northeast and panel B on the Southeast and Gulf Coast.

Second, we exploit the fact that SLR projections and awareness have significantly increased over the 2001 to 2017 sample period by focusing on intertemporal variation in the relation between SLR exposure and municipal bond credit spreads. This allows us to control for school district fixed effects that absorb any time-invariant differences across the issuers in our sample. To the extent that a relation between SLR exposure and municipal credit spreads emerges or increases as SLR projections worsen, the relation we observe is unlikely 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.[20] The yearly coefficients for Z_{bijt} control for time-varying factors including the term structure of credit spreads, the issuer's option to call bonds before maturity, and the value of bond insurance (Cornaggia, Hund, and Nguyen (2021)). Other control variables X_{bijt} include the district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues.

3.2 Main estimate of the SLR exposure premium

Table 2 presents estimates of how SLR exposure relates to municipal bond credit spreads over our 2001 to 2017 sample period. Figure 1, which shows how SLR scientific projections and uncertainty around those projections evolve over our sample period, provides context for interpreting these estimates. Between 2010 and 2017, worst-case projections range from four to five feet of end-of-century SLR, compared to less than three feet in 2001. Uncertainty and attention with respect to high-emission scenario forecasts begin a steep increase between 2011 and 2015 before falling slightly through the end of our sample.

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

We find little evidence that the relation between SLR exposure and municipal bond credit spreads changed between 2001 and 2010. After 2010, the coefficients become consistently positive, indicating that municipal bond credit spreads are higher in exposed relative to unexposed areas in the latter part of our sample, compared to the base year of 2007. From 2011 to 2013 the coefficients are all positive and mostly between 1.8 and 2.3. Between 2014 and the end of the sample in 2017, the coefficients become more statistically

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

Table 2
Effect of sea-level rise exposure on bond spreads

Panel A: Year-by-Year	(1)	(2)	(3)
SLR Exposure	−1.275**		
	(−2.05)		
SLR Exposure × 1(Year 2001)	0.061	0.313	1.238
	(0.05)	(0.36)	(0.92)
SLR Exposure × 1(Year 2002)	0.475	0.455	1.100
	(0.48)	(0.62)	(0.96)
SLR Exposure × 1(Year 2003)	−0.146	−0.203	1.435
	(−0.19)	(−0.22)	(1.10)
SLR Exposure × 1(Year 2004)	−2.343**	−2.018*	1.400**
	(−2.60)	(−1.77)	(2.08)
SLR Exposure × 1(Year 2005)	−0.655	−0.386	0.398
	(−1.24)	(−0.70)	(1.21)
SLR Exposure × 1(Year 2006)	−0.245	−0.424	−0.117
	(−0.38)	(−0.73)	(−0.22)
SLR Exposure × 1(Year 2008)	0.868	0.610	0.055
	(1.02)	(0.84)	(0.13)
SLR Exposure × 1(Year 2009)	1.911**	1.277*	0.548
	(2.26)	(1.93)	(0.62)
SLR Exposure × 1(Year 2010)	0.915	0.041	−0.068
	(0.69)	(0.03)	(−0.07)
SLR Exposure × 1(Year 2011)	2.357*	1.332	1.875
	(1.89)	(1.20)	(1.30)
SLR Exposure × 1(Year 2012)	1.956	0.930	1.911
	(0.94)	(0.43)	(1.64)
SLR Exposure × 1(Year 2013)	2.964	1.844	2.305**
	(1.34)	(0.80)	(2.03)
SLR Exposure × 1(Year 2014)	5.839*	4.852	4.747***
	(1.90)	(1.41)	(5.26)
SLR Exposure × 1(Year 2015)	5.310*	4.618	5.277***
	(1.84)	(1.40)	(4.03)
SLR Exposure × 1(Year 2016)	5.234*	4.770*	4.977***
	(2.00)	(1.76)	(2.78)
SLR Exposure × 1(Year 2017)	5.336**	4.973**	3.886**
	(2.29)	(2.23)	(2.27)
Panel B: Pooled			
SLR Exposure	−0.471*		
	(−1.80)		
SLR Exposure × 1(Post)	4.055**	3.713*	3.340***
	(2.06)	(1.78)	(3.01)
Controls	N	N	Y
County-Year-Month FE	Y	Y	Y
District FE	N	Y	Y
Outcome Mean	56.541	56.541	57.399
Outcome SD	54.304	54.304	54.594
Observations	175,415	175,415	155,212
R^2	0.3281	0.3500	0.6739
Within-R^2	0.0014	0.0010	0.1699

This table reports estimates of Equation (1) in the full sample of bonds issued by school districts in coastal states.Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators, and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. The baseline period for the district fixed effects is 2007. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *p <.1; **p <.05; ***p <.01.

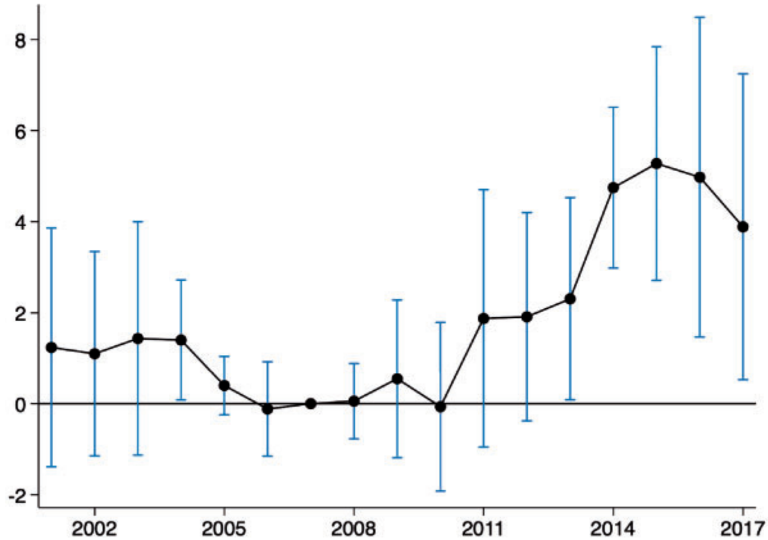


Figure 4
Effect of sea-level rise exposure on bond credit spreads
This figure plots the annual effect of SLR exposure on municipal bond credit spreads. Each point represents a coefficient from the regression specified in Equation (1), while the vertical bars represent 95% confidence bands based on standard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

significant and range from 3.9 to 5.9 across the three columns, implying that a one-standard-deviation increase in SLR exposure corresponds to a 3.9-bp to 5.9-bp increase in municipal credit spreads. Compared to the average spread of 57 bp, these estimates suggest that a one-standard-deviation in SLR exposure results in a 7% to 10% increase in municipal bond spreads by the end of our sample period.

Figure 4 provides a visual depiction of the specification in column 3. The figure reveals a generally increasing trend in the SLR exposure premium since 2010, with the premium becoming statistically significant in 2013 and more significant in 2014, after which the coefficient estimates are statistically indistinguishable from each other. This rise in the SLR exposure premium around 2014 coincides with the evidence in Figure 1. 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.[21] The figure also offers no direct evidence that our findings operate primarily through a salience channel. The rise in spreads over our sample period does not coincide directly with Hurricane Sandy, which made landfall in October 2012, or developments surrounding the Paris Climate Accord. An important caveat, however, is that it is not possible to rule out salience as a factor in explaining our results since salience may be a leading or lagging contributor to municipal bond yield spreads.

Internet Appendix Table A5 provides a number of robustness checks for our main regression. First, we confirm that the representation of states in our sample does not drive the results. Our regression coefficients are qualitatively similar after weighting the regression so that each of the 11 coastal states in our sample are equally represented. Second, we show that the estimates are qualitatively similar if we measure SLR exposure as the fraction of exposed property value (as opposed to the number of exposed properties) or if we measure exposure to four feet instead of six feet of global sea-level rise.

3.3 Long- versus short-run risks

We now consider whether the long- or short-run risk channels discussed in Section 1.2 are likely drivers of the SLR exposure premium. We begin by examining how the SLR exposure premium is affected by controlling for storm surge exposure and its interaction with the latter part of our sample period. Storm surge exposure will more directly capture short-term storm and flood risks.

The district fixed effects in our model absorb any time-invariant effect of SLR or storm surge on municipal yield spreads. These controls do not account for any time series variation in the pricing of *current* storm risk. Indeed, the shock of events like Hurricane Sandy may have prompted municipal bond purchasers to reevaluate the true risk of storm-surge related flooding in a way that coincidentally mimics worst-case scientific projections of long-run climate risks. While ex post analysis of these events reveals little, if any, long term municipal bond price effects, we include a post-by-storm surge control to mitigate the possibility that we conflate future SLR risk with present day storm surge risk.

To construct a storm surge exposure measure, 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

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

maximum storm surge height for every point along the coast in a high resolution spatial image file (raster).[22]

Before turning to our empirical analysis, it is important to consider the extent to which storm surge exposure and SLR exposure differ. The two measures are positively correlated, but clear differences are exemplified by considering the example of a peninsula. One side of the peninsula will on average be more subject to winds and tides that accompany large storms, while the two sides will be more equally affected by a general rise in sea levels. Similar variation can be obtained due to consistent weather patterns, such as wind or water currents. Thus, with sufficient cross-sectional variation, it is possible to separately identify SLR and storm surge risks. We also confirm that the storm surge data are precise enough to identify property-level price effects. We replicate tests from Bernstein, Gustafson, and Lewis (2019) in Appendix Table A8, but add in measures of storm surge risk to determine if they are similarly relevant to house prices. Across multiple models used in that paper, we find a significant and sensible discount for homes exposed to storm surge risk. We also find almost no difference in the SLR discount whether or not we control for storm urge in that setting.

To parsimoniously examine how the evolution of the SLR and storm surge exposure premiums vary over our sample period, we create a Post indicator that equals one for observations after 2012 and interact that with SLR exposure and storm surge exposure. Appendix Tables A6 and A7 show that the results are qualitatively similar, but attenuate somewhat using other definitions of the post period. In column 1 of Table 3, we establish the baseline estimate of Post $\times$ SLR in our sample. The positive and significant coefficient of 3.34 indicates that a one-standard-deviation increase in a school district's SLR exposure leads to a 3.34 larger increase in municipal bond yield spreads after 2012 compared to the early part of our sample.

In column 2 we add a control for the post period interaction with storm surge exposure. The coefficient for the Post $\times$ SLR interaction remains highly significant with a slightly larger, but statistically indistinguishable, coefficient compared to column 1. Conversely, we find little evidence that municipal bond investors have changed the pricing of storm surge risk over the same window.

Although bonds of all maturities may be influenced by SLR exposure, we expect long-maturity bonds to be affected at least as much by climate risks as short-maturity bonds. Column 3 examines this prediction by adding district-year-month fixed effects so that we compare bonds with different

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

Table 3
Effect of SLR exposure on bond spreads: Long- versus short-run risk

	(1)	(2)	(3)
SLR Exposure × 1(Post)	3.340***	3.667**	
	(3.01)	(2.06)	
Storm Surge Exposure × 1(Post)		−0.507	
		(−0.21)	
SLR Exposure × 1(Post) × Log(Maturity)			0.968**
			(2.36)
Maturity Range	All	All	All
Controls	Y	Y	Y
District FE	Y	Y	N
County-Year-Month FE	Y	Y	Y
District-Year-Month FE	N	N	Y
Outcome Mean	57.399	57.399	57.598
Outcome SD	54.594	54.594	54.470
Observations	155,212	155,212	155,212

This table reports estimates of Equation (1) with the yearly coefficients collapsed into pre-2013 and post-2012 periods. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea-level rise, normalized to zero mean and unit standard deviation. Storm Surge Exposure is the average number of feet of inundation for residential properties due to the storm surge from a Category 3 hurricane, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *p <.1; **p <.05; ***p <.01.

maturities, issued by the same school district and traded in the same month. The explanatory variable of interest is the triple interaction between SLR exposure, the post-2012 period, and the logarithm of time to maturity. 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 takeaway from Table 3 is that SLR exposure, a proxy for long-run flood risk, appears to be a more important driver of the municipal bond yield premium that has emerged since 2012 than exposure to storm surge, a specific type of short- and long-run risk.

4. Interpreting the SLR Exposure Premium

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

4.1 Structural model of municipal credit risk

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

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

In the municipal context, the bond issuer is a local government with the power to tax rather than a firm with productive assets, but the interpretation of the model is the same as in 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 cash flows, which we call the asset value, is equivalent to the market value of a firm in the discounted cash flow framework.[23]

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

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

where

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

We compute a bond's credit spread as the difference between its yield-to-maturity, which can be expressed as $y = \frac{1}{T} \ln(K/D)$, and the risk-free rate. Most municipal bonds pay coupons that are exempt from income taxation, so we use a tax-exempt risk-free rate for our calibration.[24]

[23] If the issuer were to default, bondholders would have a claim on the future stream of revenues and would recover an amount determined in a Chapter 9 bankruptcy proceeding. From the perspective of creditors, the main difference between municipal and corporate bankruptcy is that asset liquidation cannot be forced by creditors under Chapter 9. However, the assets of a firm derive their value from the ability to generate cash flows, so this distinction is really about managerial agency and corporate control, which are outside of the model. We discuss state-level policies regarding the resolution of municipal distress in Section 4.3.3.

[24] The Merton (1974) framework is usually applied to taxable corporate bond yields. Our calculation of the model parameters implied by municipal bond yields accounts for the tax exemption's effect on the pricing of credit risk. In Internet Appendix Section A4.1, we obtain quantitatively similar estimates performing the model analysis on tax-adjusted yields as in Schwert (2017), with the interest rate swap curve as the risk-free benchmark.

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

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

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

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

The failure of structural models to match the observed yields of corporate bonds has been well documented (e.g., Huang and Huang 2012). This is due to the existence of noncredit factors, D_{NC}, such as liquidity, that have a nontrivial 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 yields 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 noncredit component, D_{NC} is unrelated to credit risk, and therefore, to the asset value. Confirming this intuition, Schaefer and Strebulaev (2008) show that the Merton (1974) model provides accurate predictions of the empirical hedge ratios of corporate bonds, including high-investment-grade (e.g., AA-rated) bonds that have similar historical default rates to municipal bonds.[25]

In contrast to Schaefer and Strebulaev (2008), who study the relation between bond and equity returns, we use the model to interpret difference-in-differences regression estimates. Nevertheless, our approach is conceptually similar because we focus on the relation between changes in bond values and changes in fundamentals, as opposed to the mapping between the level of fundamentals and the level of yields. Our regression isolates the credit component of yield changes by controlling for liquidity proxies and time-varying county-level economic conditions.[26]

For empirical application of the model, we calibrate the yield change for a typical municipal bond following a change in the underlying asset value or cash flow volatility. Table 1 indicates that the mean bond in our sample has a yield-to-maturity of 3.24%, which corresponds to a credit spread of 56 bp over the maturity-matched AAA-rated tax-exempt benchmark rate of 2.68%. The average bond has 10 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.[27]

Data on the capital structure and cash flows of municipal issuers are difficult to obtain and it is impossible to observe the market value of the expected cash flow stream. Therefore, we take a flexible approach, calibrating the model to a wide range of leverage ratios (K/V in the model) and asset volatilities (σ) to match the calibrated bond yield. To obtain an appropriate set of leverage and volatility pairs, we back out the model-implied asset volatility for leverage ratios ranging from 1% to 99%. Figure 5 shows that the implied volatility is decreasing in leverage.

We use these parameter values to compute the model-implied effects of changes in the present value of cash flows or their volatility on the yield-to-maturity of a municipal bond. Panels A and B of Figure 6 present the results of this exercise for proportional changes ranging from 0% to 25%. Overall, the predictions are intuitive and indicate that yield changes are increasing in the magnitude of shocks. In general, large shocks to the underlying cash flow

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

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

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

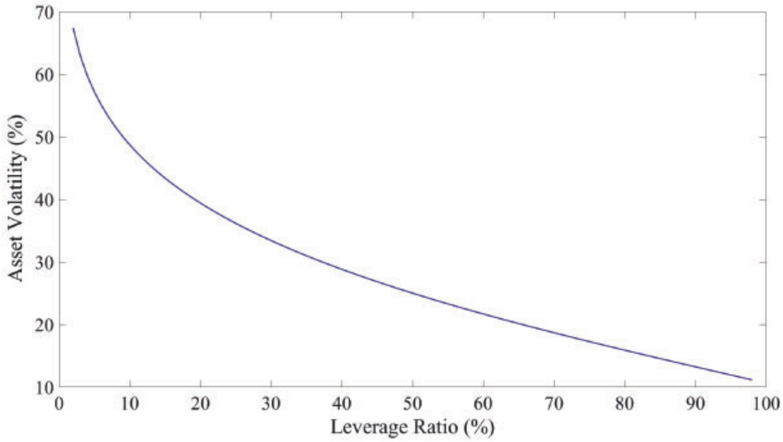


Figure 5
Model-implied asset volatility as a function of leverage
This figure plots the model-implied volatility (σ) from Equation (3) as a function of the leverage ratio (K/V). The other model parameters are $y = 3.24\%$, $r = 2.68\%$, and $T = 7.5$.

stream are necessary to generate nontrivial increases in yield, given the low level of credit risk in this market.[28]

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

Panel C of Figure 6 presents the combination of asset value and volatility shocks that correspond to the estimated 5.3-bp increase in municipal bond yields associated with one-standard-deviation higher SLR exposure in 2015 (Table 2, column 3). This estimate is in line with a reduction of 2.4% to 5.6% in the present value of the underlying cash flow stream or a proportional increase of 1.6% to 2.9% in the volatility of cash flows, depending on the issuer's

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

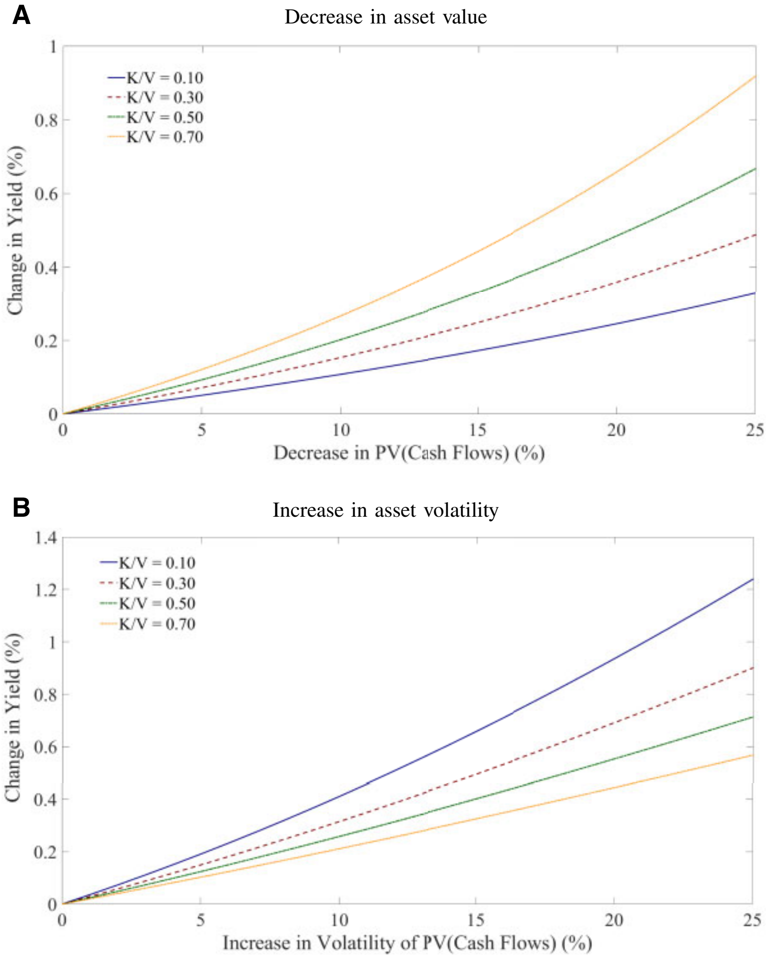
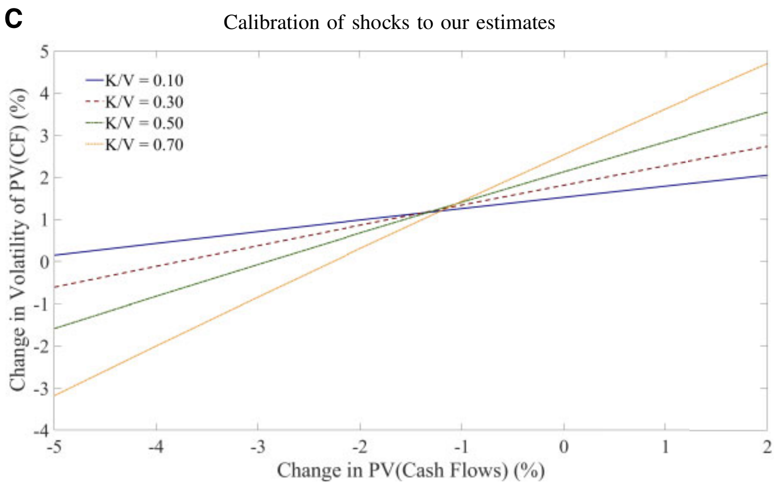


Figure 6
Effects of asset value and volatility shocks on municipal bond yields
This figure plots the change in yield associated with changes in the distribution of cash flows backing municipal bond repayment. Panel A considers reductions in the present value of cash flows, while panel B considers proportional increases in the volatility of the underlying asset value. Panel C considers the combination of asset value and volatility shocks that match our main reduced-form estimate of a 5.3-bp increase in yield. Panel D considers the combination of shocks that matches the 23.4-bp increase in yield estimated by Painter (2020). Each panel considers four parameter specifications based on leverage ratios (K/V) of 10%, 30%, 50%, and 70%, along with the associated model-implied volatilities from Figure 5. 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 $T=22.5$.

leverage and corresponding implied volatility. Naturally, a larger shock to asset value implies a smaller shock to volatility, and vice versa, holding the change in yield fixed. Taking statistical uncertainty in our estimate into account, the 95% confidence interval (2.7 bp to 7.9 bp) corresponds to asset value reductions from 1.3% to 8.1% or proportional volatility increases from 0.8% to 4.2%.



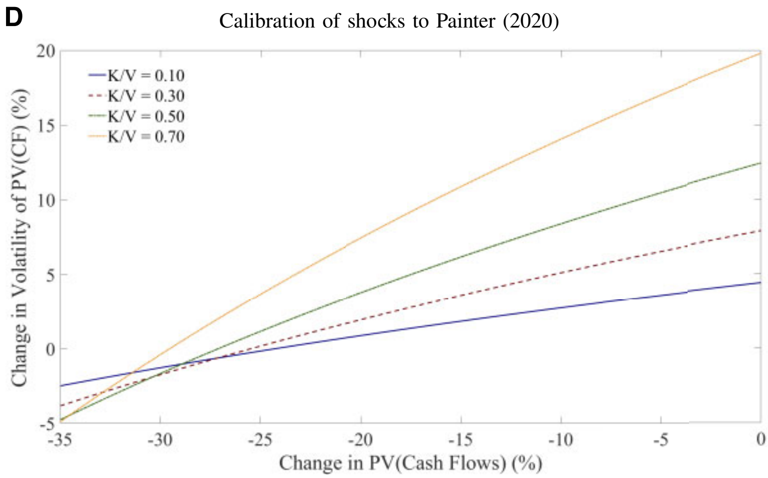


Figure 6
(Continued)

We can also use the model to shed light on the effects reported by Painter (2020), who finds that a one percent increase in climate risk, measured by Hallegatte et al. (2013) as the annual loss of GDP from sea-level rise, corresponds to a 23.4-bp increase in annualized issuance costs for bond issues with a maximum maturity of 25 years or longer. To calibrate the model, we use a sample of new issue municipal bonds from Mergent following the criteria in Painter (2020). The average yield-to-maturity of bonds with 25 years or more to maturity is 4.70% in that sample, not far from the 4.58% average issuance yield reported in table 2 of Painter (2020). The average maturity of these bonds is 30 years, which corresponds to duration of 22.5 years, and the maturity-matched AAA-rated tax-exempt benchmark rate is 4.00%.

Panel D of Figure 6 depicts the combination of shocks to the asset value and volatility necessary to produce the Painter (2020) result. Without a shock to the volatility of cash flows, this change in yield corresponds to a reduction of 25% to 30% in the present value of cash flows. On the other hand, if the reduction in cash flows is on the order of 1%, then the implied increase in volatility is between 5% and 20%. The estimates in Painter (2020) imply an economic impact that is an order of magnitude larger than the reduction in annual GDP used as his measure of climate risk, consistent with exposure to the Great Recession affecting the estimates.

While the estimates in Figure 6 are informative about the economic impact of SLR risk on exposed issuers, there is a wide range of possible effects that depend on whether SLR risk is primarily affecting current asset values or the volatility of future cash flows. In the next section, we provide auxiliary evidence to distinguish among these channels.

4.2 Asset values or uncertainty?

The model makes clear that the estimated relation between SLR exposure and municipal bond spreads could be driven by a decrease in the present value of municipal cash flows or an increase in uncertainty regarding those cash flows. Empirically, disentangling these two channels is difficult, since we only have one source of cross-sectional variation in SLR. We also only have an imperfect proxy for cash flow levels V and no direct empirical measure of cash flow uncertainty σ. Consequentially, we separate the effects of V and σ by first running direct tests on proxies for V and then indirect tests using uncertainty in scientific projections of SLR.

4.2.1 Evidence on the asset value channel. To proxy for V, we use contemporaneous residential real estate prices since the school district bonds in our sample are primarily backed by local property taxes. We view current house prices as the best available proxy for future house prices (and therefore future tax revenues) because forward looking agents should account for future growth in current prices unless that expected house price growth is connected to market level risks. We then use this house price proxy to assess whether reduced asset values can explain the SLR premium in municipal bonds. Indeed, Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020) find that SLR exposure has a negative impact on coastal home values in the second half of our sample period (and we replicate this result in Appendix Table A8). However, our research design differs from the highly localized identification strategies employed by these studies, which compare individual properties in the same geographic area that are observably similar. Those designs preclude identification of the overall effect of SLR exposure on aggregate real estate values at the school-district level because they estimate

Table 4
Effect of SLR exposure on district house prices

	(1)	(2)	(3)	(4)	(5)
SLR Exposure × 1(Post)	−0.014***	−0.103	−0.003	−0.011**	−0.015*
	(−3.06)	(−1.58)	(−0.88)	(−2.28)	(−1.89)
House Price Measure	Median	Exposed	Unexposed	Weighted	Zillow
Controls	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y	Y
Outcome Mean	12.272	3.496	12.178	12.183	12.428
Outcome SD	0.651	5.663	0.671	0.675	0.773
Observations	127,208	155,212	149,671	149,671	149,265
R^2	0.9920	0.9011	0.9894	0.9895	0.9970
Within-R^2	0.0249	0.0013	0.0128	0.0147	0.0542

This table reports estimates of Equation (1) with school district-level house prices as outcomes and the yearly coefficients collapsed into pre-2013 and post-2012 periods. Observations are at the school district-year-month level. Each district-year must have at least 50 annual house transactions recorded in ZTRAX to be included in the sample. The dependent variable is the logarithm of house price measured different ways. In column 1, Median HP is the logarithm of the annual realized median transaction price for single-family residences in the school district. In columns 2 and 3, Exposed and Unexposed Median HP is the logarithms of the annual median transaction prices for properties with nonzero and zero exposure to SLR. In column 4, Weighted Exposure HP is the logarithm of the weighted average of unexposed and exposed HP, weighted by the local share of homes exposed to SLR. In column 5, Zillow HP is the logarithm of the average of the median ZIP code house price index by Zillow in a district-year (Zillow Home Value Index available here: https://www.zillow.com/research/data/). SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea-level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators (all at the school district level), 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. *p <.1; **p <.05; ***p <.01.

the *relative* effect of SLR within a narrow geographic area. Without additional assumptions about economic spillovers, these previous local estimates do not identify the impact of SLR across districts on V. Our identification approach captures the relative differences across districts within a county, including any anticipatory effects related to beliefs about how the aggregate SLR exposure in a district will affect future local economic activity.

We first examine whether SLR exposure moves overall house prices for a school district in the same way as municipal bond yields. We consider the logarithm of three different house price measures as outcomes: (1) the annual median realized house price in a district based on transactions in ZTRAX, a general measure of house prices;[29] (2) the annual median realized house price for homes that are exposed and unexposed to six foot sea-level rise, which lets us identify whether house prices are moving mainly among exposed homes, or across all properties; and (3) the average annual Zillow house price index to capture the estimated prices of all homes (both sold and unsold) in a given year.

29 We restrict attention to school district-year observations with at least 50 house transactions recorded in ZTRAX to ensure a minimum level of data quality.

In Table 4, we replicate the estimation strategy from Equation 1, replacing the year indicators with a single post-2012 dummy. In column 1, we estimate that a one-standard-deviation increase in SLR exposure leads to a 1.4-p.p. decline in house prices in the post period. In columns 2 and 3, we split by exposed and unexposed properties, and find a 10.3-p.p. decline in house prices among exposed properties, and a drop of 0.3 p.p. among unexposed properties. These results are consistent with a large decline in house prices among exposed properties, but much smaller (and noisier) among unexposed properties. In column 4, we combine the median unexposed and exposed house price measures by weighting by the share of exposed houses and find a 1.1-p.p. decline in house prices. Finally, we find a drop of 1.5 p.p. in the Zillow house price index, consistent with the effects in the realized house prices. We then look at the graphical version of our column 1 result in panel A of Appendix Figure A5, which presents estimates of our main regression with the logarithm of annual median house prices as the dependent variable.

After the first few years of the sample period, which show a negative effect of SLR exposure on district-level house prices, the yearly SLR exposure coefficients are statistically insignificant, but trend negative for part of the period in which we observe larger bond yields. We also repeat this exercise in the remaining panels of Appendix Figure A5 for the other house price measures.

This evidence is consistent with district-level SLR exposure leading to declines in house prices across the entire school district and it suggests that declines in cash flow levels V may be an important channel for the estimated SLR yield premium. However, given the differences between the time-series patterns in Appendix Figure A5 and Figure 4, it seems possible that the changes in house prices we identify are a result of measurement error or do not reflect the same underlying economic forces as the SLR yield premium. Moreover, from a magnitude perspective, even if we assume that house prices are a perfect proxy for the present value of cash flows V backing the municipal bonds, the model from Section 4.1 suggests that the observed declines in yields correspond to movements in V that are likely larger than 1.4 p.p.

We thus push the analysis of house prices further, noting that if the effect of SLR exposure on bond spreads is due to lower house prices in exposed districts, then we should observe changes in our main coefficient as we include local house price controls in the regression (VanderWeele 2016). We test this approach in Table 5, which reports four specifications based on different methods of measuring house prices. We also address concerns about functional form by controlling for various points in the distribution of house transaction prices to fully capture the change in district house prices.

Column 1 of Table 5 reports our main specification (without house price controls) as a baseline measure of the SLR premium, with a one-standard-deviation increase in SLR exposure raising municipal bond yields by about 4 bp after 2012. Column 2 adds the logarithm of the annual median house price at

Table 5
Effect of SLR exposure on bond spreads controlling for house prices

	(1)	(2)	(3)	(4)	(5)
SLR Exposure × 1(Post)	4.181***	4.072***	4.214***	4.392***	3.715**
	(5.09)	(3.63)	(3.91)	(4.74)	(2.62)
House Price Control Measure	None	Median HP	MHP by Exposure	Zillow HP	HP Dist.
Controls	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y	Y
Outcome Mean	57.334	57.334	57.334	57.334	57.335
Outcome SD	55.285	55.285	55.285	55.285	55.287
Observations	127,208	127,208	127,208	127,208	127,197
R^2	0.6787	0.6801	0.6806	0.6796	0.6820
Within-R^2	0.1564	0.1602	0.1615	0.1590	0.1651

This table reports estimates of Equation (1), with the yearly coefficients collapsed into pre-2013 and post-2012 periods, with various additional controls for district-level house prices interacted with year fixed effects. Observations are at the bond-year-month level. Each district-year must have at least 50 annual house transactions recorded in ZTRAX to be included in the sample. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea-level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. Median HP indicates a control for the logarithm of the annual realized median transaction price for single-family residences in the school district. MHP by exposure indicates controls for the logarithms of the annual median transaction prices for properties with zero and nonzero exposure to SLR. Zillow HP indicates a control for the logarithm of the average of the median ZIP code house price index by Zillow in a district-year (Zillow Home Value Index available here: https://www.zillow.com/research/data/). HP Dist. indicates controls for the 10th, 25th, 50th, 75th, and 90th percentiles of the log of realized transaction prices in a district-year. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *p <.1; **p <.05; ***p <.01.

the district level, using realized housing transactions, interacted with year fixed effects. We see a negligible change in the SLR effect on bond yields. Column 3 partitions each district's housing transactions into SLR exposed and unexposed properties and reveals similar patterns. To account for the fact that columns 2 and 3 are based on transaction prices, column 4 uses the Zillow House Price index and aggregates the ZIP-code-level index to the school-district level. Finally, column 5 controls for the distribution of realized house prices using the 10th, 25th, 50th, 75th, and 90th percentiles. Even after this flexible control for house prices, the SLR exposure coefficient is quantitatively similar to the baseline estimate.

The takeaway from Table 5 is that controlling for district-level house prices, which should be highly correlated with the present value of local property tax revenues, has a negligible effect on the SLR exposure premium. As before, we find that a one-standard-deviation increase in SLR exposure after 2012 results in an approximately 4-bp increase in bond spreads. In Internet Appendix Figure A3, we report the year-by-year effect for the different specifications, and see two important facts: first, we see the same time-series pattern as Figure 4 across all specifications, regardless of the house price controls, we see a strong positive SLR yield premium.[30] In fact, consistent with the intuition from the structural model, the unreported relationship between house prices and municipal bond spreads is negative and statistically significant, even after controlling for district fixed effects. However, this channel appears distinct from the correlation of SLR exposure on bond spreads. Second, we see that part of what drives the small differences across columns in Table 5 are due to an increase in the SLR premium in the initial part of the sample (2001 to 2004).[31] We subsample our data into 2007 and onward and report the same models in Appendix Table A11. Here, we see even less movement in our results across different house price controls.

Overall, the evidence in Table 4 indicates that SLR does predict declines in housing values, and hence that the estimated SLR premium is potentially driven in part by reductions in V. But, this evidence is mixed, since directly controlling for this channel in Table 5 has almost no impact on the estimated SLR effect on municipal bond spreads. This suggests that uncertainty regarding future cash flows, σ, explains an important share of the SLR exposure premium in exposed school districts, especially since the magnitudes of the estimated effects in Table 4 would imply asset declines V that are too small to explain the change in bond spreads. Specifically, if we take the 1.4% reduction in house prices from Table 4 at face value as a reduction in V, then our calibrated model still implies a 1.4% increase in σ (panel C of Figure 6). Next, we examine evidence on the cash flow volatility channel.

4.2.2 Evidence on the uncertainty channel. Providing direct evidence on the role of cash flow volatility, σ, is challenging because we lack a good empirical proxy. To provide an indirect test of the impact of SLR uncertainty and volatility on bond spreads, we next examine the role of scientific uncertainty regarding SLR. Climate science analyses embed these uncertainties, both across models and within any given model (e.g., Meinshausen et al. 2009; Barnett, Brock, and Hansen 2020). As we discussed in Section 1, Garner et al. (2018) surveys the scientific literature on SLR projections and based on this survey, we construct time-series measures of the average SLR projection, the worst case or range of SLR projections, and the average within-scenario standard deviation of SLR projections. We construct these averages by first computing a study-level statistic and then averaging across all studies over a 2-year period.

In panel A of Table 6, we integrate these measures into the regression outlined in Equation (1). To do so, we interact the annual value for each of these measures with an area's SLR exposure. This provides a time-varying

30 In Appendix Figure A3, we omit 95% confidence intervals to ease comparisons, but include them in Appendix Figure A4, where we control for log(Median HP) interacted with year fixed effects.

31 This mechanically would induce a smaller effect in the post period since the post effect is compared relative to the 2001–2011 period.

Table 6
A. Effect of SLR exposure based on time variation in academic forecasts

	Univariate	Bivariate			
	(1)	(2)	(3)	(4)	(5)
Frac Exposed X Mean Forecast	−0.338	−0.686*	−1.054*	−2.340**	−0.361**
(All Risk, 2yr)	(−0.85)	(−1.84)	(−1.98)	(−2.28)	(−2.28)
Frac Exposed X St. Dev. of Forecasts	1.806***	1.880***			
(All Risk, 2yr)	(4.42)	(4.38)			
Frac Exposed X Range of Forecasts	0.943***		1.311***		
(All Risk, 2yr)	(3.44)		(3.22)		
Frac Exposed X Worst Forecast (2yr)	0.862***			2.458***	
	(3.28)			(2.72)	
Frac Exposed X St. Dev. of Forecasts	1.262***				−0.872
(Med Risk, 2yr)	(5.49)				(−1.30)
Frac Exposed X St. Dev. of Forecasts	1.896***				2.658***
(High Risk, 2yr)	(4.26)				(2.76)
Articles for Projection	All	All	All	All	All
Controls	Y	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y
Outcome Mean	66.381	66.381	66.381	66.381	66.381
Outcome SD	56.894	56.894	56.894	56.894	56.894
Observations	118,694	118,694	118,694	118,694	118,694

(*Continued*)

measure of SLR risk for each region, where the time variation varies according to different components of the forecast. The first column presents these coefficients when estimated separately in Equation (1). Columns 2 through 5 include each dispersion measure along with the mean. Across all columns in the first row of Table 6, we find little evidence that the average SLR projections from scientific studies during a year predicts higher municipal bond spreads in exposed areas. This corroborates the takeaway from Table 5 that the documented relation between SLR projections and municipal yield spreads is not primarily due to the effect of expected future SLR.

The remainder of panel A of Table 6 examines how the combined measures of SLR uncertainty and projected SLR levels relate to municipal bond yield spreads. Whether or not we include measures of the average SLR projections in our regressions, we consistently find a positive relation between measures of uncertainty or downside risk and yield spreads. This result holds using measures of the standard deviation, range, or worst-case forecasts. Appendix Table A9 shows that the estimates are similar whether or not we use the procedure in Appendix Section A1 to select the most relevant studies or whether a 1- or 2-year window is used for a study's inclusion.

The results relating to our standard deviation measures are consistent with investors paying most attention to worst-case scenarios and the information in these worst-case scenarios being highly correlated with information contained in less extreme scenarios. The time series of within-scenario forecast uncertainty with respect to mid-level scenarios positively predicts municipal bond yield spreads, but this effect is subsumed if included alongside a measure

Table 6
(Continued)

B. Attention-weighted uncertainty

	(1)	(2)	(3)
Frac Exposed X Attention Weighted Mean (2yr)	0.078		−0.629*
	(0.33)		(−1.84)
Frac Exposed X Attention Weighted St. Dev. (2yr)		1.847***	2.058***
		(4.37)	(4.15)
Controls	Y	Y	Y
County-Year-Month FE	Y	Y	Y
District FE	Y	Y	Y
Outcome Mean	66.381	66.381	66.381
Outcome SD	56.894	56.894	56.894
Observations	118,694	118,694	118,694

This table reports estimates of Equation (1) where, instead of collapsing the yearly coefficients into a pre/post indicator, we interact school district SLR exposure with measures of SLR expectations derived from scientific forecasts. Observations are at the bond-year-month level and the sample begins in 2007 because of a lack of SLR projections prior to that time. The measures of SLR projections are generated from the studies in Garner et. al (2018). *Mean forecast* takes the mean SLR projection for every scenario in a study and computes the study-level average. Then it takes the average of those study-level averages across all studies in a 2-year period. *SD of forecasts* performs a similar 2-year aggregation for the mean standard deviation of SLR projections across all scenarios in a study. We similarly construct standard deviation measures using only medium and high emissions scenarios, respectively. *Worst forecast* is the highest projection from each study, averaged across all studies for a 2-year period. *Range of forecasts* is *Worst forecast* minus a similar computation using the lowest SLR projection in each study. Attention-weighted mean and standard deviation are calculated as described in Section 4.2.2. First, we obtain from Google Scholar the ratio (r) of the number of studies which discuss high forecast models (RCP8.5 or SRES A) divided by the total number of studies which cite medium or high scenarios (e.g., RCP 8.5, RCP 4.5, SRES A, and SRES B). We then calculate the attention-weighted variables as follows:

$$Attention\,Weighted\,Mean = r * Mean(High\,Risk) + (1-r) * Mean(Med\,Risk)$$

$$Attention\,Weighted\,StDev = r * StDev(High\,Risk) + (1-r) * StDev(Med\,Risk)$$

The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea-level rise, normalized to zero mean and unit standard deviation. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

of forecast uncertainty for high-level scenarios. The concentration on worst-case scenarios is consistent with uncertainty being relevant to bond investors to the extent that it reflects downside risk.

The findings in Table 6 suggest that uncertainty in SLR projections, and in particular downside risk or worst-case scenarios, are a very relevant component of SLR projections for municipal yield spreads. The similarity between the time series of the SLR exposure yield spread premium (see Figure 4) and the evolution of uncertainty and worst-case scenarios in the scientific literature (see Figure 1) further illustrates this takeaway.[32] Our findings offer suggestive evidence that uncertainty regarding SLR, rather than the level of SLR forecasts,

32 It is in fact notable that there is a slight dip in the effect of SLR in our sample, consistent with a small decline in the standard deviation of projections in the last 2 years of the sample.

is driving municipal bond yields higher toward the end of our sample period. The correlation between the mean SLR prediction across all models and the average within-model standard deviation in our sample is 0.39, low enough to assuage fears of multicollinearity in our independent variables. Thus, the findings in Table 6 indicate that within-model uncertainty plays a role in the recent rise in municipal credit spreads for SLR exposed areas.

Next, we consider whether the results above are driven by within-scenario uncertainty in scientific projections or the attention paid to the different emission scenarios. We consider the evidence in panel C of Figure 1, which indicates that scholars began discussing more dire scenarios around the same time that scientists' within-scenario uncertainty was increasing. The intuition in Barnett, Brock, and Hansen (2021) would suggest that as more attention is paid to more severe scenarios, investors' expected loss will increase even if the mean SLR projections remain unchanged.

In our next set of tests, we incorporate the attention being paid to various scenarios into the time-series measures of SLR projections. Specifically, we reconstruct our "mean" and "standard deviation" measures to account for the ratio of attention between the RCP 4.5 and 8.5 scenarios. Our attention weighted measures are calculated as follows:

$$\text{Attention-Weighted Mean} = r \times \text{Mean(High Risk)} + (1-r) \times \text{Mean(Med. Risk)}$$

$$\text{Attention-Weighted StDev} = r \times \text{StDev(High Risk)} + (1-r) \times \text{StDev(Med. Risk)}$$

where r is the ratio of RCP 8.5 scenario mentions to the total mentions of the RCP 4.5 and 8.5 scenarios.

In panel B of Table 6, we run a similar analysis as in panel A using the attention-weighted measures. In column 1 we find that the attention-weighted mean emissions do not interact with SLR risk to drive credit spreads. Directly accounting for a shift in attention to more severe climate scenarios does not change our finding that mean predictions appear unrelated to increasing SLR related spreads. Column 2 further indicates that incorporating attention into the standard deviation measure also results in a similar interaction coefficient to that in panel A. Lastly, a comparison of both measures results in a positive weight on the standard deviation term. Thus, accounting for the shift in attention across scenarios does not meaningfully change any of our conclusions from panel A.

Both panels of Table 6 bolster the narrative that uncertainty around SLR is the primary driver of increased spreads for SLR exposed districts in the later part of our sample. Pinpointing whether the effect is driven more by attention to more risky or uncertain scenarios or by widening risk within scenario is not possible given the correlation between attention and within-scenario risk. In unreported analysis, we find that both channels seem to be at play with neither dominating. The role of σ as a channel for SLR's impacts on bond spreads is a unique finding for our paper in the climate finance literature, as prior studies have focused on the impact of expected SLR on asset values. Because of the structure of municipal bonds, the growth in uncertainty about climate change and SLR may trigger much sharper reactions in municipal bond pricing than in the pricing of other assets (e.g., house prices). This suggests an important role of using a variety of asset classes, and especially contingent claims on other assets, to study markets' views on sea-level rise.

4.3 Mediating channels: Local beliefs, tax reliance, and distress policies

Our estimates thus far suggest that uncertainty regarding the future economic impact of SLR is the most likely driver of the recent rise in municipal yield spreads for exposed areas. In this section, we consider cross-sectional heterogeneity in this effect. First, we use state-level segmentation in the municipal bond market to explore the role of heterogeneous investors' beliefs in the pricing of climate risk. Second, we examine the local tax regime, which determines how real economic shocks affect school district budgets. Finally, we discuss the role of state-level policies on municipal distress, which affect how local government funding shortfalls translate into creditor losses.

The factors discussed in this section are not mutually exclusive. On the contrary, we observe a positive correlation between state-level beliefs about climate change, local tax regimes, and policies on municipal distress. Therefore, we encourage a cautious interpretation of our results and the following discussion. Moreover, any heterogeneous effects that do exist raise the potential for the estimated effect of SLR exposure that we have discussed in previous sections to change if certain segments of the market change their beliefs or the composition of the sample changes.

4.3.1 Heterogeneous investor beliefs. The relation between SLR exposure and municipal yield spreads that we document is driven by investors' beliefs regarding the future economic impact of climate change. We argue above that investors' beliefs about the relative municipal bond payoffs in SLR exposed areas are related to uncertainty in scientific SLR projections. Here, we examine the extent to which heterogeneity in investors' beliefs about climate change risks play a role in how SLR exposure is priced in the municipal bond markets. Bernstein, Gustafson, and Lewis (2019) and Baldauf, Garlappi, and Yannelis (2020) find that climate change beliefs affect how real estate markets price SLR exposure. The municipal bond setting lends itself to examining how heterogeneous state-level climate change beliefs relate to municipal bond pricing because buyers are often local retail investors due to the tax advantages of in-state ownership (Schultz 2012).

To measure an area's beliefs about climate change, we merge our data with the Yale Climate Opinion Maps (Howe et al. 2015). Specifically, we aggregate 2014 county-level survey data on responses to the question "worried about global warming" to the state level, weighting each county by the number of school districts it contains. We aggregate to the state level instead of using

Table 7
Effect of SLR exposure on bond spreads by local beliefs

	(1)	(2)	(3)
SLR Exposure × 1(Post)	5.159***	−0.883	4.210***
	(6.48)	(−0.61)	(5.04)
SLR Exposure × 1(Post) × State Worry			2.961***
			(3.02)
Level of Concern	Worried	Not Worried	All
Controls	Y	Y	Y
District FE	Y	Y	Y
County-Year-Month FE	Y	Y	Y
Outcome Mean	66.416	66.353	66.381
Outcome SD	56.505	57.209	56.894
Observations	53,398	65,296	118,694
R^2	0.6846	0.6566	0.6640
Within-R^2	0.1324	0.2117	0.1802

This table reports estimates of Equation (1) with the yearly coefficients collapsed into pre-2013 and post-2012 periods, and an added interaction with state residents' level of concern about global warming. Observations are at the bond-year-month level. Worried states in column 1 include (in order of concern) New York, Massachusetts, New Jersey, Rhode Island, Connecticut, and Maine, while Not Worried states in column 2 include Texas, North Carolina, South Carolina, Mississippi, and Louisiana. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea-level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. State Worry is a measure of global warming concerns from the Yale Climate Opinion Map, normalized to zero mean and unit standard deviation. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. * p <.1; ** p <.05; *** p <.01.

the county-level data directly because the segmentation of municipal bond investors is driven by state-level tax policy. To form our State Worry measure, we then subtract the average state's level of worry and divide by the standard deviation, resulting in a standardized measure that ranges from −2.39 to 0.87.

In columns 1 and 2 of Table 7, we partition the sample based on whether a state's worry about climate change is above or below the median. Above-median states include (from most to least worried) New York, Massachusetts, New Jersey, Rhode Island, Connecticut, and Maine, while below-median states include Texas, North Carolina, South Carolina, Mississippi, and Louisiana. The SLR exposure premium since 2013 is positive and statistically significant in states with an above-median level of worry. In less worried states, the SLR exposure premium is statistically insignificant and in the opposite direction in the later part of our sample. In column 3 of Table 7, we examine whether the differential effect of SLR exposure is significantly different in worried states in the latter part of our sample by augmenting the specification from Equation (1) to include a triple interaction between SLR exposure, the post-2012 period, and the state's level of worry about climate change. Consistent with columns 1 and 2, we find that the post-2012 SLR exposure premium is significantly larger in worried states relative to less worried states. The evidence in Table 7 suggests a similar role for climate beliefs that prior researchers have observed in housing markets.

Table 8
Effect of SLR exposure on bond spreads by tax regime

	(1)	(2)	(3)
SLR Exposure × 1(Post)	2.409*	−2.315	−0.290
	(1.83)	(−1.06)	(−0.43)
SLR Exposure × 1(Post) × Property Tax Rate	1.042**		
	(2.13)		
SLR Exposure × 1(Post) × School Local Funding		6.095***	
		(2.93)	
Sample	Main	Main	CA
Controls	Y	Y	Y
District FE	Y	Y	Y
County-Year-Month FE	Y	Y	Y
Outcome Mean	66.381	66.381	83.533
Outcome SD	56.894	56.894	63.107
Observations	118,694	118,694	101,071
R^2	0.6637	0.6639	0.6946
Within-R^2	0.1797	0.1800	0.1755

This table reports estimates of Equation (1), with the yearly coefficients collapsed into pre-2013 and post-2012 periods, and an added interaction with measures of school districts' reliance on property taxes. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea-level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. Property Tax Rate is the effective property tax rate at the state level, normalized to zero mean and unit standard deviation. School Local Funding is the fraction of school funding drawn from within the school district, normalized to zero mean and unit standard deviation. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *p <.1; **p <.05; ***p <.01.

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

Table 8 presents a test of this channel. In column 1 we interact SLR exposure with the post-2012 indicator and the average property tax rates for the state. We find that states with higher property tax rates exhibit larger credit spread increases in SLR-exposed districts. To address the concern that differences in tax rates do not reflect differences in dependence on property tax revenue, column 2 replaces property tax rates with the proportion of school funding coming from local sources. We find that school districts which are more reliant on local revenue streams have experienced larger increases in credit spreads associated with SLR exposure.[33]

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

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

4.3.3 State policies on municipal distress. Our findings suggest that SLR risk increases default risk, with investors pricing higher expected losses (i.e., higher default probability or lower expected recovery) for SLR exposed issuers toward the end of our sample period. Each state has its own policies on the ability of its municipalities to default on their debt, which could have implications for the relation between SLR risk and municipal default risk. Gao, Lee, and Murphy (2019) categorize states by whether they allow municipalities to file for Chapter 9 bankruptcy (South Carolina and Texas, in our sample), have "proactive" policies that offer assistance to distressed municipalities while discouraging Chapter 9 bankruptcy (Maine, New Jersey, New York, and North Carolina), or lack policies regarding financial distress (Connecticut, Louisiana, Massachusetts, Mississippi, and Rhode Island).[34] These authors show that proactive policies are associated with lower default rates, higher creditor recoveries, and lower credit spreads relative to the Chapter 9 approach. Thus, it is important to understand how these policies affect the pricing of SLR risk. Table 9 partitions the sample according to the classification in Gao, Lee, and Murphy (2019) to assess how these policies correlate with the SLR exposure premium. Column 1 shows a slightly larger SLR premium in states with proactive distress policies relative to the full sample, while column 2 shows a statistically insignificant effect in Chapter 9 states. Column 3 shows a highly significant negative SLR premium in states with no explicit distress policies, though we should note that this group composes only 3% of the sample observations. The final column includes an interaction effect confirming that the SLR premium is significantly larger in proactive states. Considering the effect of proactive distress policies in

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

Table 9
Effect of SLR exposure on bond spreads by state distress policy

	(1)	(2)	(3)	(4)
SLR Exposure × 1(Post)	5.282***	−0.886	−14.657***	−1.496
	(6.52)	(−0.61)	(−3.98)	(−1.13)
SLR Exposure × 1(Post) × 1(Proactive)				6.524***
				(4.58)
Distress Policy	Proactive	Chapter 9	Neither	All
Controls	Y	Y	Y	Y
District FE	Y	Y	Y	Y
County-Year-Month FE	Y	Y	Y	Y
Outcome Mean	66.017	66.205	76.085	66.381
Outcome SD	56.103	57.292	60.687	56.894
Observations	51,247	64,008	3,439	118,694
R^2	0.6781	0.6569	0.7862	0.6640
Within-R^2	0.1333	0.2127	0.1858	0.1804

This table reports estimates of Equation (1), with the yearly coefficients collapsed into pre-2013 and post-2012 periods, and an added interaction with indicators for state-level policies regarding municipal distress. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the Municipal Market Advisors AAA-rated tax-exempt benchmark curve, in basis points. SLR Exposure is the fraction of residential properties that would be inundated by six feet of sea-level rise, normalized to zero mean and unit standard deviation. 1(Post) is an indicator equal to one for observations occurring after 2012 and zero otherwise. State distress policies are coded according to Gao, Lee, and Murphy (2019): Proactive states include Maine, New Jersey, New York, and North Carolina; Chapter 9 states include South Carolina and Texas; and Neither states include Connecticut, Louisiana, Massachusetts, Mississippi, and Rhode Island. Controls include the logarithm of the bond's time to maturity, callability, and insured status interacted with year indicators; and district-level average income, the number of years since issuance, the ratio of trading volume to amount outstanding, the standard deviation of transaction prices by bond-month, and an indicator for general obligation issues. t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *p <.1; **p <.05; ***p <.01.

isolation, it is surprising to see that the SLR exposure premium is concentrated in states with proactive policies. However, the same states—New Jersey and New York, in particular—are more concerned about climate change and rely more on local property taxes to fund schools. The results in Table 9 suggest that these other mediating channels outweigh the effect of more supportive distress policies. In the absence of state support, we would expect to see even larger effects of SLR exposure on municipal bond spreads because bondholder losses in default would be greater in the areas where we see price effects. To quantify this counterfactual, we extend the structural model of credit risk to include bankruptcy costs in Internet Appendix Section A4.2. When bankruptcy costs are higher, as in a Chapter 9 state relative to a proactive state, a reduction in asset values or an increase in volatility has a larger impact on credit spreads. However, this is a second-order effect: a 10% increase in bankruptcy cost, analogous to the difference in recoveries between Chapter 9 and proactive states documented by Gao, Lee, and Murphy (2019), leads to a proportional increase of approximately 3% in the effect of fundamental shocks. In a related vein, the financial health of state governments could affect the likelihood of conditional transfers to exposed school districts. Particularly relevant are the unfunded public pension liabilities that Rauh (2016) estimates are worth \$3.8 trillion. However, most states fund teachers' retirement plans at the state level, so it is unlikely that pension funding has a differential effect on SLR exposed and unexposed school districts in the same county. If pension funding were directly affecting our estimates, then we would expect to see large price effects when portfolio values collapsed during the financial crisis, as in Novy-Marx and Rauh (2012), which we do not. Nevertheless, there is a risk that underfunded pensions reduce the likelihood of intergovernmental transfers conditional on a local shock, which would offset the slight attenuation of the SLR premium from state-level support for distressed municipalities.

5. Conclusion

This paper uses the municipal bond market to study the extent to which the risk of sea-level rise is priced in financial markets. In line with the evolution of scientific consensus and popular concern about this risk, we find that the market begins to price SLR exposure in 2013, after which we observe that exposed issuers have significantly higher borrowing costs than unexposed issuers. In 2015, a one-standard-deviation increase in SLR exposure corresponds to a 5.3-bp increase in credit spreads. We observe significant effects at both short and long maturities, with stronger effects for long-maturity bonds. The lack of similar effects based on measures of short-term flood risk suggests that long-run SLR risk is the primary driver of our results.

In addition to addressing the question of how SLR risk affects municipal borrowing costs, a contribution of this paper is to adapt a structural model of credit risk from the corporate finance literature to interpret the SLR exposure premium and quantify the economic fundamentals that could explain it. Our methodology can be applied in other situations to interpret the effects of economic shocks on risky debt prices, even in settings where it is difficult to observe the issuer's capital structure and the market value of its assets.

We find that the increase in expected default losses attributable to SLR risk is low, but that the economic impact is nontrivial, equivalent to a reduction of 2.4% to 5.6% in the present value of local government cash flows or a proportional increase of 1.6% to 2.9% in the volatility of these cash flows. We conclude that municipal bond investors are mainly pricing the uncertainty and downside risks associated with SLR's future impact rather than the effects of reduced asset values today. These estimates shed light on the importance of downside uncertainty in SLR risk, and the extent to which better information and modeling can work alongside climate remediation efforts in coastal communities.

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