Measuring Cities' Climate Adaptation

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Abstract

Adaptation by cities is critical in reducing the inevitable impact of climate change. Here we present the first large-sample evidence of cities' adaptation to elevated flood risk, a key consequence of climate change. We construct and analyze a new linguistic measure of adaptation extracted from financial disclosures for 431 US cities over 2013-2020. While cities with a higher flood risk have higher adaptation, many high-risk cities are still under-prepared: more than half of high-risk cities have below-average adaptation levels. We explore three factors associated with this *adaptation gap*, defined as having a lower level of adaptation than what is expected based on the flood risk faced by the city. Contrary to concerns about the political divide in climate change responses, we do not find that Republican cities are more likely to have an adaptation gap. Instead, we find strong evidence that cities' financial constraints are associated with the adaptation gap: cities with one standard deviation smaller unrestricted-fund-to-expense ratio are 4.8% more likely to have an adaptation gap. We also find support for a novel factor, myopic planning horizon, where cities with a one-year-shorter horizon are 4% more likely to have an adaptation gap. Such myopia may explain why cross-sectional tests show that state grants do not fully mitigate financial constraints.

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1 Introduction

Climate change poses an imminent threat to humanity's vulnerability to rising sea levels, higher temperatures, and other negative consequences of changing weather patterns (1). It is unlikely that these challenges could be avoided even under the optimistic scenario of limiting global warming to 1.5°C. The places with a high concentration risk and population have to *adapt*— i.e., invest in reducing the harmful impact of climate change. This underscores the urgency of concerns about the existence of the adaptation gap, the difference between current levels of adaptation and the levels needed to reduce the impacts of climate risks (1).

Understanding the factors behind the adaptation gap is crucial to inform policymaking in the wake of escalating climate risks. However, systematic evidence on the adaptation gap has been hindered by data scarcity. The details of cities' existing infrastructure and future adaptation plans are not readily available and must be collected at the individual city level. Because of data limitations, the existing literature either examines case studies, conducts surveys, or uses socio-economic variables to approximate adaptation (e.g., 2; 3; 4; 5).

Here we provide large sample evidence on the adaptation gap by extracting and analyzing adaptation data from 8,762 hand-collected financial disclosures of 431 US cities over 2013-2020. US cities are required to regularly report audited financial disclosures that contain material information about adaptation, which guarantees that all significant existing and future adaptation programs will be picked up by textual analysis. For our textual analysis, we created and validated a dictionary specifically designed to capture city-specific hard and soft adaptation strategies. To study the adaptation gap, we combine this textual data with independent flood risk assessments, hand-collected partisanship data, as well as financial and socio-economic city characteristics (see Methods).

We examine three factors potentially contributing to the adaptation gap: political partisanship, financial constraints, and planning horizon. First, the literature finds that partisanship is a major factor shaping attitudes toward climate change-related policies in the US (6; 7; 8; 9; 10). If Republican constituents place a lower probability on climate hazards due to their political views, we would see lower levels of adaptation in cities with Republican leaders. On the other hand, responsible managers are expected to plan ahead and assess future hazards, make preparations, and invest in adaptation measures, especially in areas with high flood risk. If political affiliation does not change climate-change risk assessment but merely affects the partisan rhetoric, we would observe no difference in real adaptation actions between Republican and non-Republican cities.

Second, financial constraints limit the available resources for a city to invest in the necessary infrastructure, technology, or programs to adapt to the impacts of climate change. Tackling climate risks is costly: according to a recent survey conducted by Climate Disclosure Project (CDP), an average climate project costs $63 million, and among cities that did not have an adaptation plan, 25% cite financial constraint as a barrier (11). The Sixth Assessment Report from the Intergovernmental Panel on Climate Change (IPCC AR6) deems the lack of financial resources as a key constraint with high confidence (1; 12). As such, we expect cities with limited funding and credit to be more likely to have an adaptation gap.

While adaptation is costly, there is an economic benefit to investing in adaptation for 90% of the world's coastal population (13). This raises the puzzle as to why cities are under-investing in adaptation. One reason is the lack of access to up-front funding even though adaptation projects are financially beneficial in the long run. As our third factor, we examine another reason: myopic planning horizon. If the length of a city's budget planning horizon is limited, it may not allow the city to consider long-term risks (such as climate risk) in its decision-making. This idea is similar to corporate myopia, where more frequent and short-term financial disclosure causes managers to make myopic decisions, such as under-investing in long-term capital expenditure (14; 15; 16). We predict that cities with a shorter-term outlook for capital projects are more likely to have an adaptation gap. Such myopia can be a result of financial constraints, where cities with a higher interest rate put more emphasis on short-term returns, and can also relate to other governance frictions. Importantly, this planning horizon factor would suggest that providing funding alone may not mitigate the adaptation gap.

2 Results

We follow the literature and divide adaptation into two categories: hard and soft adaptation (17; 18; 19; 20; 21; 22). Hard adaptation includes building physical infrastructure and upgrading existing infrastructure, such as seawalls and drainage systems. Soft adaptation involves using natural solutions, such as beach nourishment and mangrove restoration, to decrease flood risk.

To quantify adaptation at the city level, we created a city-specific adaptation dictionary and leveraged it to conduct a textual analysis of a comprehensive collection of financial disclosures (including budgets, annual reports, and bond prospectuses) that were gathered manually. Our dictionary contains 147 keywords in three categories: hard adaptation, soft adaptation, and general adaptation (see **Supplementary Table 1** for the keywords and Online Appendix A for more details). General adaptation includes phrases that represent climate adaptation but cannot be classified into soft or hard adaptations, such as “flood relief” and “flood reduction”.

Our main adaptation measure is the number of adaptation sentences in budgets and annual reports per city-year. We select this measure to ensure consistency of our measure across city years, as US cities prepare both the budget and the annual report every year. We identify 3,161 city-year observations from 431 cities with both the annual report and the budget (**Supplementary Table 2**). For each city-year, we combine information from budgets and CAFRs to create three metrics:

(1) *main adaptation*, which is the total count of general, hard, and soft adaptation sentences, (2) *hard adaptation*, which is the number of hard adaptation sentences, and (3) *soft adaptation*, which is the number of soft adaptation sentences. Among this sample, 2,011 city-years also have at least one bond prospectus. For this subsample, we separately create a measure labeled as *main+bond*, which is the total count of general, hard, and soft adaptation sentences from budgets, CAFRs, and bond prospectuses. In the subsequent text, we will refer to our constructed adaptation measures as italicized *adaptation* for conciseness.

After analyzing all 8,762 sample documents, we identified 79,771 sentences that contain adaptation keywords. The 3,161 city-years have an average of 19.18 *main adaptation* sentences in their budgets and CAFRs, with a mean of 15.20 *hard* and 0.58 *soft adaptation* sentences (**Supplementary Table 3**). As most soft adaptations are only feasible for coastal cities, we restrict our analysis of *soft adaptation* to cities located in coastal states. Consistent with cities discussing adaptation actions in their budget's capital improvement plans, budgets have the highest average *adaptation* of 15.08 sentences, while CAFRs contain an average *adaptation* of 3.43 sentences. Our second measure, which incorporates bond prospectuses, has a mean of 28.40 sentences over 2,011 city-years, confirming our intuition that bond prospectuses add new information about cities' adaptation. **Supplementary Figures 1 and 2** illustrates the variation in *adaptation* over time and across different states.

To ensure that *adaptation* captures meaningful variation in cities' actions, we conduct several validation and robustness tests (see Methods and Online Appendix B for more details). First, we show that cities with higher *adaptation* receive a larger insurance discount in a program that rewards communities that are more prepared against flood risks. Second, we find evidence that *adaptation* is positively correlated with a city's expenses from capital improvement and emergency-related funds. Third, we replicate prior research that shows climate risk is priced in municipal bond spreads (23; 24) and find that *adaptation* mitigates the positive association between climate risk and bond spreads. To further confirm the validity of our measures, we conduct robustness analyses where we adjust the definition of *adaptation* to exclude the most common keywords (drainage and stormwater) and a falsification analysis with a placebo measure unrelated to climate risks that captures police and public safety. We also conduct sensitivity tests using alternative measures such as groups of keywords and the number of keywords (Online Appendix C).

2.1 Topics of adaptation

The most commonly used adaptation-related terms are those associated with stormwater management and drainage, followed by references to flood-related measures. Other frequently utilized groups of keywords pertain to adaptation infrastructure, such as seawalls, inlets, and levees (**Figure 1A**).[1]

Topics of adaptation sentences vary across document types, with budgets (**Figure 1B**) mostly describing the roles of departments and programs related to adaptation and the details of capital improvement projects, CAFRs (**Figure 1C**) focusing on funding allocation, and bond prospectuses (**Figure 1D**) discussing the intended use of funds. The relative importance of these topics is relatively stable over time within each document type (see Methods and Online Appendix D for more details).

2.2 Adaptation and flood risk

We first examine whether cities with higher flood risks are engaging in more adaptation to gauge the prevalence of an adaptation gap. We find a strong correlation between flood risk and *main, hard, soft,* and *main+bond* adaptation in the regression analyses that account for population, document size, and state- and year-fixed effects (**Supplementary Table 4A**). The relationship is most evident in coastal regions, particularly the Gulf Coast (**Figure 2A**). A ten percent rise in flood

[1] We group the keywords based on common unigrams. For example, both flood control and flood management are part of the keywords group "flood."

risk is linked to a 4.4% increase in adaptation in 2013, with this connection becoming progressively stronger over time, reaching 9.4% in 2020 (**Figure 2B**). When we examine hard and soft adaptation separately, we observe that flood risk had the greatest correlation with soft adaptation in 2016, which then plateaued. However, for hard adaptation, the connection steadily grew over time (**Figure 2C**).

Moreover, cities in the top quartile of flood risk increase their *main adaptation* by 20% following the exposure of major hurricanes, further confirming that flood risk is one of the defining factors in adaptation decisions (**Supplementary Table 4B**). This result is consistent with previous research demonstrating that significant events can draw attention to a particular issue and prompt proactive action in response (e.g., 25; 26; 27).

2.3 Factors related to the adaptation gap

While adaptation is positively correlated with flood risk, our data find the existence of an adaptation gap: among cities with more than 10% of properties under flood risk, for more than half of them, *main adaptation* is less than that of an average city with flood risk lower than 10%. We further examine the factors associated with this adaptation gap. It is challenging to determine which cities have a "true" adaptation gap, as estimating the optimal adaptation level for a particular city is difficult. However, it is possible to measure the relative adaptation gap, which represents how far a city is from adaptation levels predicted based on flood risk. We first estimate the predicted level of adaptation based on a linear regression model with flood risk, population, and length of disclosures for a given state and year. We then define *adaptation gap* as an indicator variable that is equal to one when the actual adaptation is lower than the predicted adaptation.

Contrary to concerns about the partisan divide in climate change beliefs (6; 7; 8; 9; 10), we do not find that Republican cities are more likely to have an *adaptation gap* across all dimensions except for *soft adaptation gap* that is 10% more likely to be observed in cities with a Republican city leader (**Figure 3A** and **Figure 4**). These findings suggest that having a Republican city leader does not necessarily lead to decreased investment in hard adaptation, but it may affect the city's decisions regarding using nature-based solutions, such as beach nourishment or restoration of coral or oyster reefs.

Instead, we find evidence that financial constraint and shorter planning horizons are correlated with having an *adaptation gap*. Cities with one standard deviation lower unrestricted-fund-to-expense ratio are associated with a 4.8% higher chance of having an *adaptation gap* (**Figure 4**). This result holds for both *hard adaptation gap* (7.2%) and *soft adaptation gap* (11.2%), where the latter magnitude is larger, potentially because we limit the sample to cities in coastal states. We do not find similar results between the adaptation gap and debt per capita, except for *soft adaptation gap*. The prediction for debt per capita is less clear because high debt can represent a limited ability to raise additional funds or that the city might have already raised debt to invest in adaptation. Additionally, the explanatory power of financial constraints on the adaptation gap reduces over time (**Figure 3B**).

We find strong evidence that cities with shorter planning horizons are more likely to have an adaptation gap, and this effect persists over time (**Figure 3C**). Cities with a one-year shorter budget planning horizon are 4% more likely to have an *adaptation gap* (**Figure 4**). This result holds for *hard adaptation gap* (3%) but not for *soft adaptation gap*.

2.4 Heterogeneity in adaptation gap distribution

2.4.1 Flood risk

Financial constraints are more important for cities in high-flood-risk areas (**Figure 5A**). Both high- and low-flood-risk cities have smaller adaptation gaps when they have higher planning horizons. Political beliefs do not have a significant relationship with the *adaptation gap* in either case.

2.4.2 Constituents' beliefs

Financial constraint is also binding in cities located in counties where there are more constituents who believe that local officials should do more to address climate change (according to the data from 2021 Yale Climate Opinion Survey, **Figure 5B**). One interpretation is that in cities where the capital constraint is more binding, the citizenry is more concerned and expects their city leaders to do more adaptation. Partisanship and planning horizon does vary in importance in areas with different beliefs.

2.4.3 State grants

If financial constraints explain low adaptation in certain cities, the availability of state grants might mitigate this constraint. To examine the role of state grants, we manually collect information about state grants available for cities to fund their climate adaptation projects.

State grants cannot fully mitigate the financial constraints (**Figure 5C**). While the coefficient magnitude on *UFB/Total Expense* is smaller in states with large grants, the coefficient remains negative and significant.

2.4.4 Local Household Income

Variation in average household income does not change the relationship between *adaptation gap* and political affiliation, capital budget outlook, and unrestricted fund balance (**Figure 5D**). The ability to raise debt is more likely to be a constraining factor for cities where household income is lower.

3 Discussion

Here we provide the first large-sample evidence that underscores the prevalence of an adaptation gap among US cities. This gap is primarily related to financial constraints and myopic planning horizon, but not partisanship. As emphasized by IPCC AR6, closing the adaptation gap is a key issue, especially for cities, which are our front-line defense against geomorphological climate risks (1). IPCC AR6 describes the adaptation gap referencing Olazabal et al. (2019)'s finding that over 50% of the 136 largest coastal cities did not implement policies stated in the standalone adaptation documents (4). Olazabal et al. (2019) acknowledge the lack of panel data on cities' climate adaptation, which our systematic textual-analysis method addresses and provides us with a larger sample size and comparability to better examine constraints in adaptation.[2]

It is important to understand constraining factors associated with the adaptation gap as it may help policymakers tailor policy solutions. One surprise is that political affiliation is not significantly associated with having an adaptation gap, which is in contrast to existing climate mitigation studies that find partisanship is a major social barrier in the US (6). One potential reason is that political divides are more common in climate mitigation, where certain words like "greenhouse gas" and "climate change" are more politically charged. Another reason is that Republican cities are less likely to mention climate change but nonetheless address flood risks that can affect the local economy and residents well-being.

We find strong evidence that capital constraint is related to the adaptation gap. Furthermore, our cross-sectional test shows that state grants do not mitigate this constraint. This finding highlights the importance of studying funding channels that can alleviate capital constraints, including private financing and public-private partnership. In validating our adaptation measures, we find that municipal market prices "adaptation' mitigates the flood risk premia (Online Appendix Table B1C). Future studies can also examine the role of traditional and green bonds in facilitating the

[2]Out of 17 US cities that Olazabal et al. (2019) searched for, they were only able to locate standalone adaptation policies for 11 cities. In contrast, all of their 17 cities are in our sample, and some of them score highly on our adaptation measure using financial disclosures. For example, out of 17 US cities they examined, Olazabal et al. (2019) did not find relevant adaptation policies for Houston, Portland, Providence, San Diego, San Jose, and Tampa. Our data show that Tampa, FL has high levels of adaptation according to the budget.

funding of adaptation projects.

Myopic planning horizon is also significantly related to the adaptation gap. Notably, higher discount rate implied by financial constraint is only partly related to the planning horizon: the correlation between planning horizon and unrestricted-fund-to-expense ratio is just 12%. Therefore, while improving funding access can partially ease the constraint related to myopic planning, it will probably not provide a complete solution. Myopic planning is likely associated with governance issues, stickiness of planning horizons, electoral terms, and behavioral factors. Consequently, a policy intervention can involve fostering governance practices and implementing better planning mechanisms that account for the long-term, such as mandating five or ten-year budget forecasts.

In sum, our paper calls attention to closing the adaptation gap by addressing capital constraints and myopic planning horizons. While our findings do not establish causation, we offer a preliminary investigation of the adaptation gap by introducing novel measures of adaptation. Our measures are based on a textual analysis of municipal disclosures, which ensures accuracy and enables comparison across cities and over time. Future studies can establish causal links between adaptation gap and city characteristics. Our methodology can be extended to global samples as cities' financial disclosures should be publicly available, albeit with variations in national requirements. Researchers can use our measures to better understand cities' adaptation efforts (or lack thereof), a topic emphasized in IPCC AR6. Households and firms can use our data to locate cities with adaptation gaps to help them make better decisions and demand local governments to adapt or facilitate local governments with their respective constraints.

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4 Methods

4.1 Textual measure of adaptation

We define adaptation as city's actions to lower the damage from immediate and future flood hazards, which reduces the geomorphological flood risk faced by the city. We obtain this definition by narrowing down a more general definition by IPCC AR6 in the context of cities and flood risk (1).[3]

We make two choices when developing our textual analysis methodology: we use a dictionary-based approach for textual analysis (28), and we focus on one dimension of climate risk—flood risk. Dictionary-based approach provides a simple and transparent interpretation of our textual measures and is used in recent literature examining climate risks in the corporate setting (29; 30).

We explore adaptation to flood risk for three reasons. First, flood risk is a direct result of climate change, with warmer temperatures leading to heavier precipitation, more hurricanes, and rising sea levels (31). Second, flood risk is the most salient risk faced by the cities and dominates other risks in terms of both the numbers and damage costs (32). And finally, flood risks can be addressed by investing in a specific set of infrastructure solutions (e.g., 33; 19), which allows us to develop a precise dictionary of keywords that capture adaptive actions related specifically to flood risk.

Following the existing climate science literature, we consider two categories of adaptation: hard adaptation and soft adaptation (e.g., 17; 18; 19; 20; 21; 22). Hard adaptation involves the construction of physical infrastructure and improvements to the existing infrastructure. Such infrastructure is intended to either limit the extent of the city's flooding (e.g., seawall) or to enhance the city's ability to channel the water so that stormwater doesn't flood the city (e.g., drainage systems). Hard

[3] IPCC AR6 definition in the main report: Adaptation is defined, in human systems, as the process of adjustment to actual or expected climate and its effects in order to moderate harm or take advantage of beneficial opportunities. In natural systems, adaptation is the process of adjustment to actual climate and its effects; human intervention may facilitate this (1).

adaptation involves high capital investment, but can be effective immediately once construction completes (19).

Soft adaptation involves the use of nature and sediment-based solutions to reduce flood risks, such as beach nourishment, bioswales, and mangrove restoration. Relative to hard adaptation, soft adaptation has potential benefits on the wider ecosystem conservation and may also be more aesthetically beneficial for tourism (19). However, the dependency on nature involves a longer duration and relies on the availability of natural resources (e.g., sand) (22).

4.1.1 Adaptation dictionary

Our dictionary contains three types of keywords: general adaptation, hard adaptation, and soft adaptation. General adaptation includes general phrases that represent climate adaptation but cannot be classified into soft or hard adaptations, such as “flood relief” and “flood reduction”.

To create our adaptation dictionary, we first thoroughly read and extract a list of initial keywords and phrases from diverse sources that detail adaptation strategies that can be applied to cities. Specifically, we gather initial keywords and phrases from the following documents: (i) the cities 2020 reporting guidance in the Carbon Disclosure Project (CDP), (ii) the city climate hazard taxonomy issued by the C40 Cities Climate Leadership Group, (iii) the climate change summary for policymakers issued by the Intergovernmental Panel on Climate Change (IPCC), and (iv) relevant academic papers that focus on climate change adaptation (e.g., 17; 34; 18; 35; 19; 20; 21; 36).

Next, we expand our initial keyword list by incorporating adaptation-related keywords used by cities that are not present in the sources previously mentioned. To do this, we read through the financial disclosures of a selected subset of cities over time in order to find additional relevant words for our keyword list. The subsample includes nine cities in Massachusetts, five cities in

Florida, and Washington, DC.[4] This process allows us to capture words and phrases that local governments use to describe their climate adaptation actions, but which may not be commonly used in guidance and reports issued by other organizations. Examples of adaptation keywords obtained through this process include "detention storage systems" and "stormwater improvement."

Following Li et al. (2020), we use single-word unigrams and two-word bigrams to form a hybrid dictionary that we then apply in our textual analysis (29). To validate that none of our unigrams are irrelevant, we extract all of the bigrams that contain a given unigram, and then manually examine the most frequent bigrams and unigrams. During this process (described in Online Appendix A), we update our list of keywords if we find any that are frequently used in irrelevant phrases and sentences.[5] Our resulting dictionary contains 147 adaptation-specific words and can be found in **Supplementary Table 1A**. **Supplementary Table 1B** provides examples of sentences that contain words from the general, hard, and soft adaptation dictionaries.

4.1.2 Sample

Our sample contains both coastal and non-coastal cities. Coastal cities are especially vulnerable to the impacts of climate change, including sea-level rise and increased frequency and intensity of coastal storms. These impacts can lead to increased flood risk, shoreline erosion, and damage to infrastructure, homes, and businesses. However, including non-coastal cities is also important because climate risks exacerbate the chances of heavy rainfall, rising water levels in rivers or lakes, or rapid snowmelt (37; 38; 39). Inland cities are also vulnerable to flash floods, which can result from intense rainfall over a short period of time.

We collect municipal financial documents spanning 2013-2020 for 449 cities in 48 states and

[4] We chose random cities in Massachusetts and Florida because these two states are exposed to relatively high flood risk. We added Washington, D.C. to the sample because it is not directly on the shore but has high flood risk exposure and outlines its planning approach in detail. Massachusetts cities: Boston, New Bedford, Quincy, Cambridge, Newton, Somerville, Salem, Beverly, Revere. Florida cities: Fort Lauderdale, Miami, Miami Beach, Orlando, and Tampa.

[5] **Table A1** presents the relative frequency of the keywords from our constructed dictionary.

the District of Columbia. Our data collection focuses on cities located in states along the East and Gulf coasts, where the risk of flooding is higher. In particular, we have obtained financial information from cities that meet three criteria: they have financial data available in Muni Atlas, flood risk data from First Street Foundation, and a population of over 40,000 people, as recorded in the 2010 census. For the remaining states, to ensure the feasibility of our data collection, we have selected cities with populations of 80,000 people or higher.[6] We have restricted our sample to larger cities because smaller cities often only provide budget information in the form of tables rather than detailed documents, limiting comparability with cities that provide the full budgets. Because we were not able to locate both the annual report and budget documents for certain cities, our final sample contains 431 cities. On average, cities in our sample have a population of 234,100, where 8.64% (or 8,126) of properties are at risk of flooding (see **Supplementary Table 2**). Flood risk is salient for cities in both coastal and non-coastal states: 37% of coastal and 32% of non-coastal cities have more than 10% properties exposed to flood risk.

4.1.3 Financial disclosures data

Financial disclosures are uniquely positioned to provide comprehensive and verifiable information about cities' adaptation over time. Financial disclosures are required to be regularly posted and contain material information about adaptation. This guarantees that every significant project or plan will be picked up by our textual analysis without the discretion of selective disclosure. These characteristics of financial reporting make it a more valuable source of information for analysis compared to other types of text, such as standalone adaptation plans that are voluntarily published by a subset of cities and are not typically updated annually. Another advantage of using financial disclosures is the ability to capture both forward-looking and backward-looking information. Specifically, in annual reports, cities discuss conditions of the current adaptation infrastructure. In

[6] We further augment our sample to include the cities used in Dagostino and Nakhmurina (2022) (40).

budgets and bond prospectuses, cities provide forward-looking information about planned adaptation projects for addressing climate risks. These reports also include historical adaptation as cities maintain the adaptation projects, such as by setting up "seawall funds."

The primary source of CAFRs and bond prospectuses is the Electronic Municipal Market Access (EMMA) website. We download the annual budgets and CAFRs that are not available on EMMA from the current city government's website or from its Wayback Machine version. If the disclosures are not available online, we obtain the documents by contacting city officials directly. We convert these disclosures into a format that is amenable to text analysis by cleaning and preprocessing the data. Further details about our data-cleaning methodology can be found in Online Appendix E.

4.2 Validation

To ensure that our measure of climate adaptation (*adaptation*) accurately captures meaningful variation in cities' actions, we conduct several validation and sensitivity tests. We summarize findings here and include a detailed discussion of each validation test in the Online Appendix B. Each validation test involves a subset of cities with data availability, which contrasts with our textual measure with availability for all cities. First, we test if *adaptation* is correlated with lower flood insurance premiums. We find that cities with higher *adaptation* receive a larger insurance discount in a program that rewards communities that are more prepared against flood risks (**Table B1 Panel A**). Second, we test if a higher level of *adaptation* translates into increased spending on infrastructure projects. We find evidence that *adaptation* is positively correlated with a city's expenses from capital improvement and emergency-related funds (**Table B1 Panel B**). Third, we replicate prior research that shows climate risk is priced in municipal bond spreads (23; 24) and find that *adaptation* mitigates the negative association between climate risk and bond spreads (**Table B1 Panel C**). We replicate these three validation tests using a placebo textual measure based on the number of sentences about safety and do not find the results above (**Tables B2 and B3**).

4.3 Other data

4.3.1 Flood risk

We use flood risk data from the First Street Foundation, a non-profit organization that measures America's flood risks using scientific research and technology. They predict long-term weather patterns and map detailed geomorphological data in order to estimate the likelihood of flooding. More specifically, we use their 2020 National Flood Risk Assessment data, which captures the percent of properties that face a substantial risk from any type of flooding event, including storm surges, high tides, and the rise in sea level. Substantial risk is defined as a more than 1% annual probability of flooding that reaching 1 cm or higher, which is the same measure used by the Federal Emergency Management Agency (FEMA). Since these data are available at a zipcode level, we aggregate the data to a city level by adding up the total number of properties and the properties at risk, and then by calculating the percent of properties at risk at the city-level. To illustrate what this measure captures, we use cities in Florida as an example: Miami (coastal) has an incredibly high flood risk of 40%, while Orlando (inland) has a somewhat lower, but still substantial flood risk of 6%.

4.3.2 City characteristics and financial data

Financial and demographic data come from Muni Atlas, which has information on local governments that has $50 million in debt outstanding. For financial variables, we use data on city's outstanding debt and fund expenses. For demographic variables, we include annual population, which Muni Atlas collects from the American Community Survey that is published once a year. As a partitioning variable, we use the average income per household from Muni Atlas. From Muni Atlas, we also retrieve the six-digit CUSIP numbers associated with each city, which helps us identify bond prospectuses on EMMA.

4.3.3 Planning horizon

We use the number of years a city plans ahead for in its capital budget outlook to proxy for the planning horizon. We manually extract the number of years presented in a city's capital budget plan by reading through each budget document. As an illustration, Online Appendix F provides a sample capital improvement budget table for the city of Tampa, which had a capital budget outlook of five years in the budget prepared for the fiscal year 2018.

4.3.4 Political affiliation

Our data on political affiliation combines the data from OurCampaigns.com (used in Nakhmurina, 2020) with the hand collected data for city-years where the city leader (mayor or city manager) or her political affiliation was not found on OurCampaigns.com (41).[7] To gather this data, we first identified the names of the city leaders in power during a specific year. Next, we searched for their political affiliation on the city's website, in news articles, and by contacting the cities directly. The final data has three categories: *Republican*, *Democratic*, and *Other*. The first two categories identify the representatives of corresponding parties, and *Other* refers to the city leaders who identify as independents or belong to another party.

4.3.5 Local climate opinions

We use the 2021 Yale Climate Opinion Survey data, which provides county-level beliefs about climate change in the US. We use the county-level responses to the following prompt to capture people's concern about the impact of climate change: "Your local officials should do more to address global warming." We take the percentage of the respondents who agree with this statement and label it *Local Officials*. In the cross-sectional regression, we use the median value of *Local Offi-*

[7]Different cities have different organizational structures. The majority of the U.S. cities are governed under either council-manager or mayor-council structures. In mayor-council cities, mayor is endowed with significant administrative and budgeting authority. The main governing power in the council-manager cities is delegated to the city manager, that is overseen by the city council. While mayor in council-manager cities is also elected, she only has ceremonial powers. We collect partisan information for the city leaders that have decision-making power.

cials as the partitioning variable.

4.3.6 State grants

We manually search for the availability of state grants that cities can apply for to invest in adaptation. Since the way grants are presented involves much heterogeneity, to compare across states, we identify the largest monetary value of a grant a city can receive in each state (*State Grant*). In the cross-sectional regression, we use the median *State Grant* of $ 65,000 as the partitioning variable.

4.4 Estimating adaptation gap

To examine the prevalence of the adaptation gap, we first regress *adaptation* on flood risk. We estimate the following equation:

$$\begin{aligned} Adaptation_{i,t} = \beta_1 Flood\,Risk_{i,t} + \beta_2 Log(Population)_{i,t} + \beta_3 Log(N\,Sentences) \\ + Fixed\,Effects_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where $Adaptation_{it}$ is the number of adaptation sentences for city i at year t. To reduce the influence of a few keywords with high frequency, we winsorize all our adaptation measures at the 99th percentile. $Flood\ Risk_{it}$ is the percent of properties subject to flood risk. We control for a city's population and the total number of sentences in the financial reports. We take the logarithm for these two control variables to resemble a normal distribution. We include state-fixed effects and year-fixed effects to control for time-invariant changes in each state and for time trends.

We rely on the outcome of this regression to estimate the adaptation gap (supplementary **Table 4A**). We define *Adaptation Gap* indicator variables as equal to one if the residuals from the **Table 4A** regression are negative. To examine the factors related to having an adaptation gap, we run the following regression:

$$\begin{aligned} Adaptation\,Gap_{i,t} = \beta_1 Republican_{i,t} + \beta_2 UFB/Total\,Expense_{i,t} + \beta_3 Log(Total\,Debt\,per\,Capita) \\ + \beta_4 Capital\,Budget\,Outlook_{i,t} + Fixed\,Effects_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where *Adaptation Gap*$_{it}$ is an indicator that equals to one if the residual from the **Table 4A** regression is negative. We also conduct a sensitivity test using alternative definitions of *Adaptation Gap*, where we require the residual to be smaller than -0.5 and -1 (Online Appendix G). *Republican*$_{it}$ is an indicator variable equal to one if the city has a Republican city leader. *UFB/Total Expense*$_{it}$ is unrestricted fund balance scaled by total expenses, a measure that describes the amount of funds relative to the total expenses that are not restricted in any way and can be spent however the city chooses to.[8] *Total Debt per Capita*$_{it}$ is the total debt outstanding scaled by the population of the city. *Capital Budget Outlook*$_{it}$ is the reported number of years in the capital budget. We include state-fixed effects and year-fixed effects to control for time-invariant changes in each state and for time trends. Our sample in this analysis is slightly smaller because some cities do not have *UFB/Total Expense* and *Total Debt per Capita* in Muni Atlas.

4.5 Salient climate events and adaptation

Previous research demonstrates that significant events can draw attention to a particular issue and prompt individuals to take proactive action in response (e.g., 25; 26).[9] We identify the first time $1 billion hurricane events hit the U.S. states using the U.S. Billion-Dollar Weather and Climate Disasters data from the NOAA National Centers for Environmental Information (NCEI) (32). We use these data to compare our textual measure for cities with low (control) and with high (treatment) flood risks within a state. We expect that after a hurricane, cities with a higher flood risk will have a higher *adaptation* than cities in the control group. Specifically, we test:

$$\begin{aligned} Adaptation_{i,t} = {} & \beta_1 High Flood Risk_{i,t} + \beta_2 High Flood Risk_{it} \times Post_{i,t} + \beta_3 Log(Population)_{i,t} \\ & + \beta_4 Log(N Sentences) + Fixed Effects_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

[8] In contrast, restricted fund balance is the portion of total fund balance that is either non-spendable or restricted for a particular use. GFOA recognizes the importance of having sufficient amounts of unrestricted fund balances for the cities prone to natural disasters: https://www.gfoa.org/materials/fund-balance-guidelines-for-the-general-fund.

[9] For example, we observe an increase in adaptation for cities in Florida starting in 2016, which is the year Hurricane Matthew struck and caused six deaths and significant damages (42).

where $Adaptation_{it}$ is the number of adaptation sentences for city i at year t. $High\ Flood\ Risk_{it}$ is an indicator that equals one if the city's flood risk belongs to the upper quartile within a state. $Post_{it}$ is an indicator that equals one for observations after which the state experienced the first hurricane identified in the NCEI dataset. We control for the size and resources of the cities by including the logarithm of the annual population from Muni Atlas and the logarithm of the total number of sentences. We include state-year fixed effects to account for time-varying local conditions. We cluster standard errors by the state to address the potential correlation within states.

4.6 Limitations

In this work, we do not account for certain forms of adaptation that are difficult to quantify through textual analysis of financial disclosures, such as zoning, building codes, or migration-related measures. This is because those measures are not always outlined in financial disclosures, but are outlined in other policy documents. However, sometimes the best response to increased flood risk is to retreat. We encourage future research to examine these important dimensions of adaptation.

Our focus in this study is on adaptations to flood risk. However, it's important to note that climate risks to cities can manifest in various forms beyond just flood risk, including exposure to extreme temperatures, droughts, and wildfires. Further research can explore adaptation to these forms of climate risk.

Figure 1: Adaptation themes.
Panel A shows the most common keyword groups, along with their relative appearance frequency. To form the groups, we allocate all our dictionary words based on common keywords. For example, any expressions that contain the word "flood" is part of the flood group. We display the top seven categories and group the rest into "Other".

Panel A: Most common adaptation keyword groups.

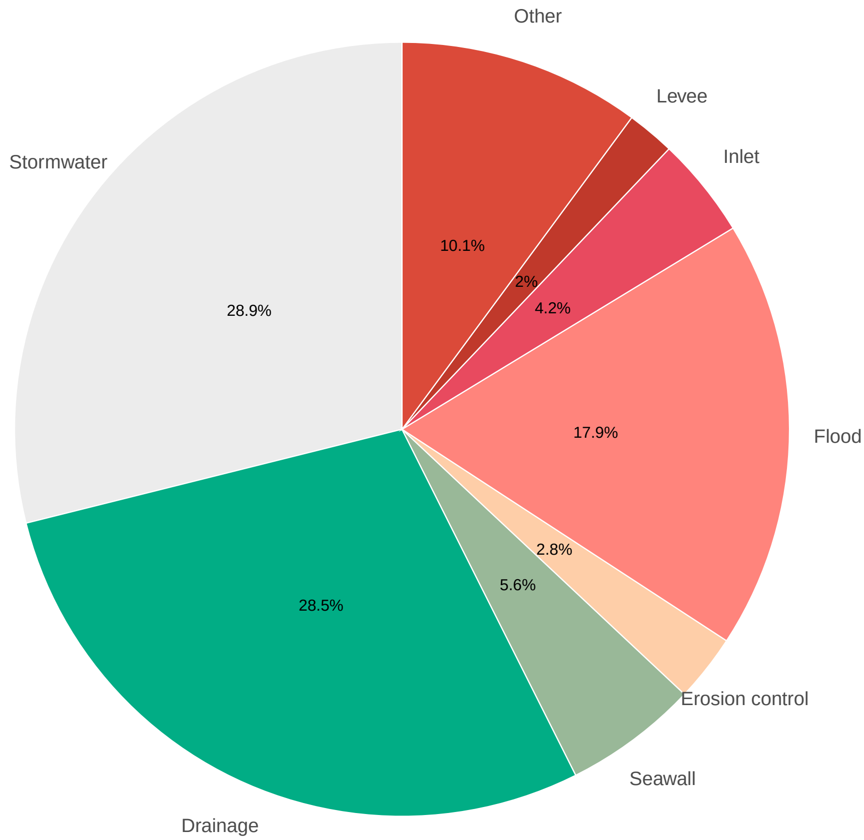
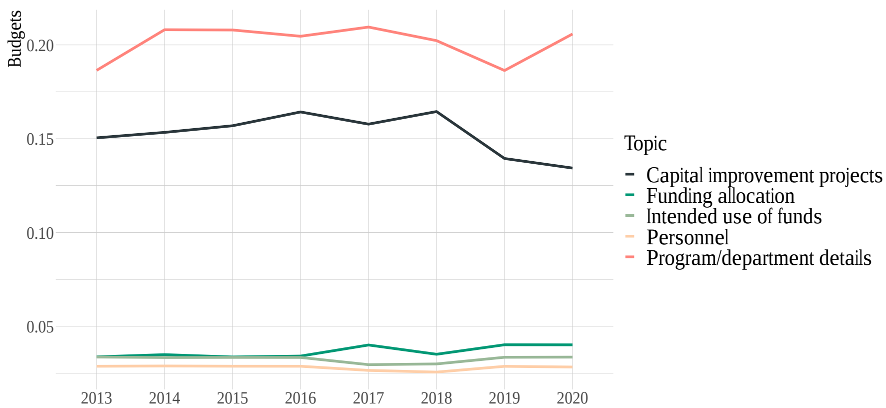
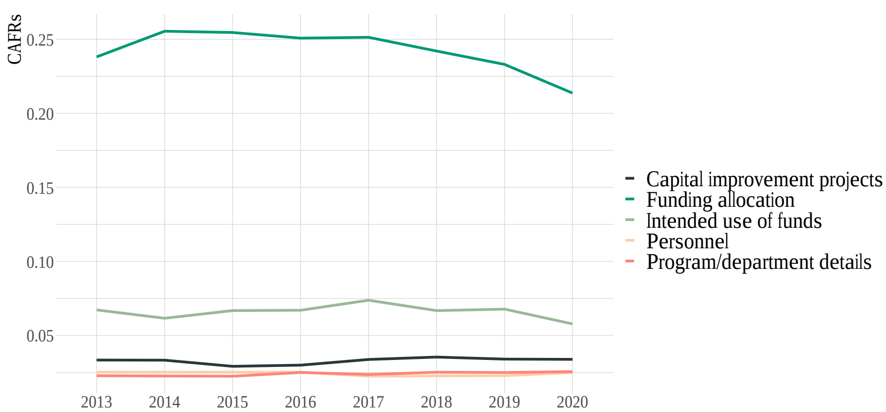


Figure 1: Adaptation themes, continued.
Panels B, C, and D present five main topics extracted using LDA from the sample of adaptation sentences in budgets (Panel B), CAFRs (Panel C), and bond prospectuses (Panel B) over the sample period, 2013-2020. To better identify topics, we exclude sentences that are likely tables from the text data. *Capital improvement projects* captures sentences that describe details on the proposed capital improvement projects, such as repairing or installing catch basins. *Funding allocation* covers descriptions of the funds spent or funding allocation for the capital projects. *Intended use of funds* captures the remaining tables that were not removed using our table identification approach. These sentences pertain to adaptation-related projects or districts and specify the intended use of funds. *Personnel* captures generic sentences that list the names of personnel. *Program/department details* provides details on the role of departments or programs related to adaptation, such as inspecting and managing stormwater capital improvement projects. We plot medians of topic loading values across documents over time.

Panel B: Budgets



Panel C: CAFRs



Panel D: Bonds

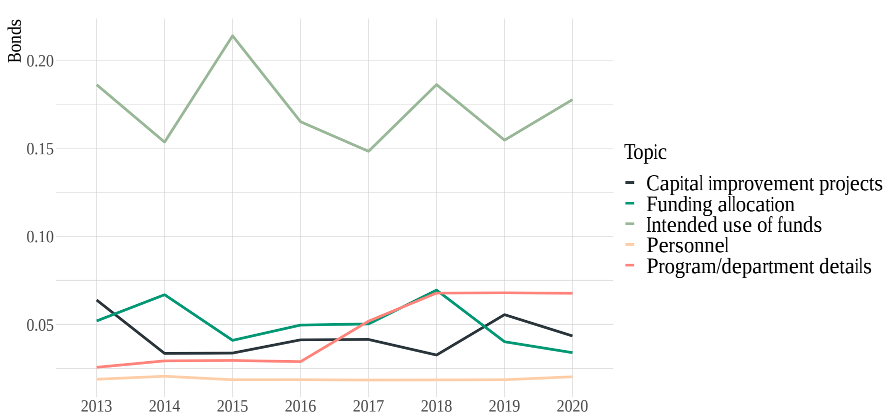
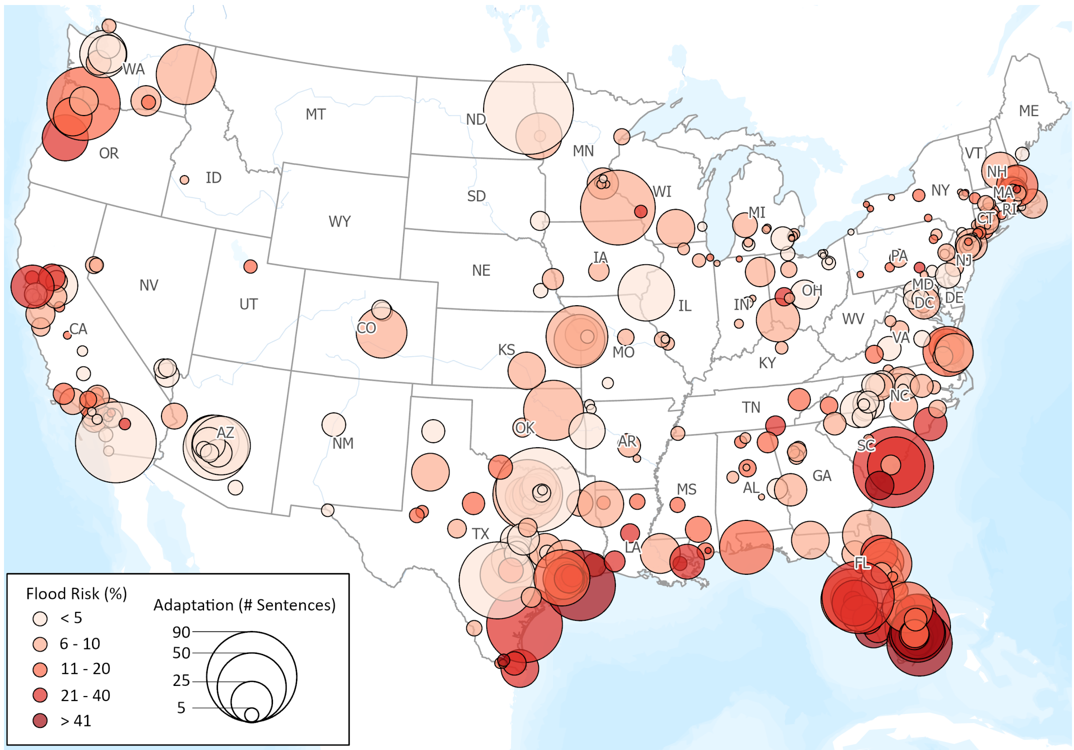
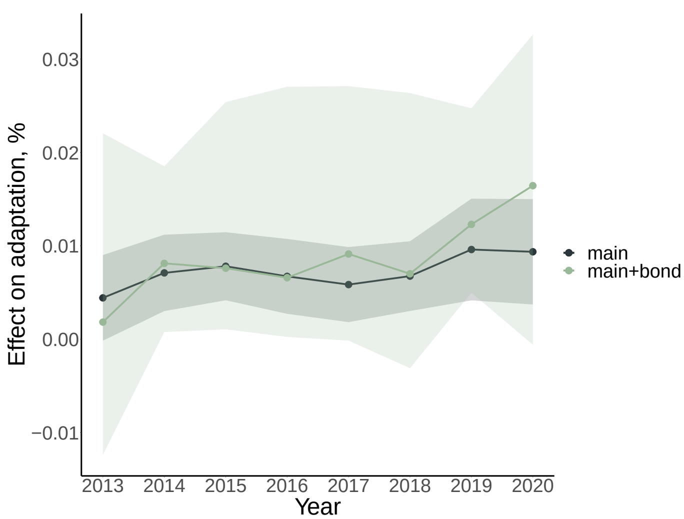


Figure 2: Cities with higher flood risk do more adaptation.
Panel A maps *main* adaptation measure for our sample cities. The size of the bubble increases as adaptation measure increases, and the color intensifies with higher flood risk. Panels B and C plot point estimates of the effect of flood risk on adaptation, following eq. (1). Shaded region is 95% confidence intervals. Panel B displays the results for *main* and *main+bond* measures. Panel C shows results for *hard* and *soft* adaptation.

Panel A: Map of adaptation and flood risk



Panel B: Flood risk and *main* adaptation



Panel C: Flood risk and *hard* and *soft* adaptation

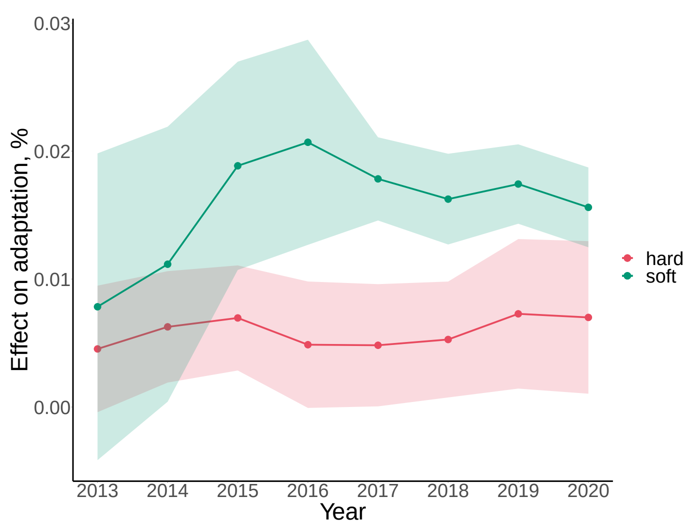
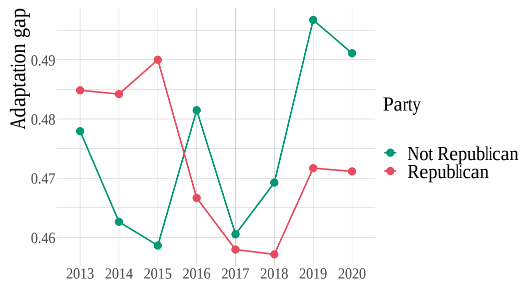
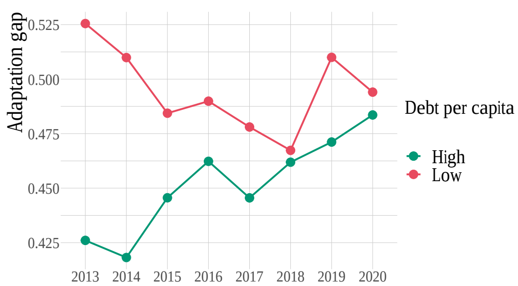


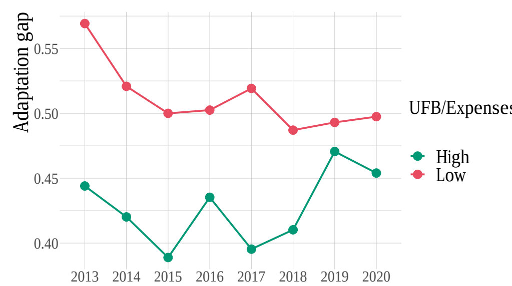
Figure 3: Adaptation gap over time.
This figure presents mean *main adaptation gap* over the sample period, 2013-2020. Panel A plots adaptation gap by political affiliation. Panel B plots adaptation gap split by whether cities' financial ratios is above the medians of debt per capita and the ratio of unrestricted fund balance to total expenses. Panel C plots adaptation gap by whether cities' capital budget outlook is above median.

Panel A: Political affiliation



Panel B: Credit constraint





Panel C: Capital budget outlook

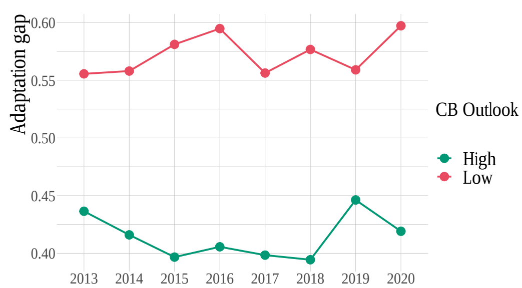


Figure 4: Determinants of adaptation gap.
This figure plots the estimates of the eq. (2). We plot coefficients for *main, hard, soft, and main+bond adaptation gap*. *Republican* is an indicator variable equal to one if the city has a Republican mayor. *UFB/Total Expense* is unrestricted fund balance scaled by total expenses. *Total Debt per Capita* is total debt outstanding scaled by the population of the city.*Capital Budget Outlook* is the reported number of years in the capital budget. Bands indicate 95% confidence intervals. Full regression results are presented in Supplementary Table 5A.

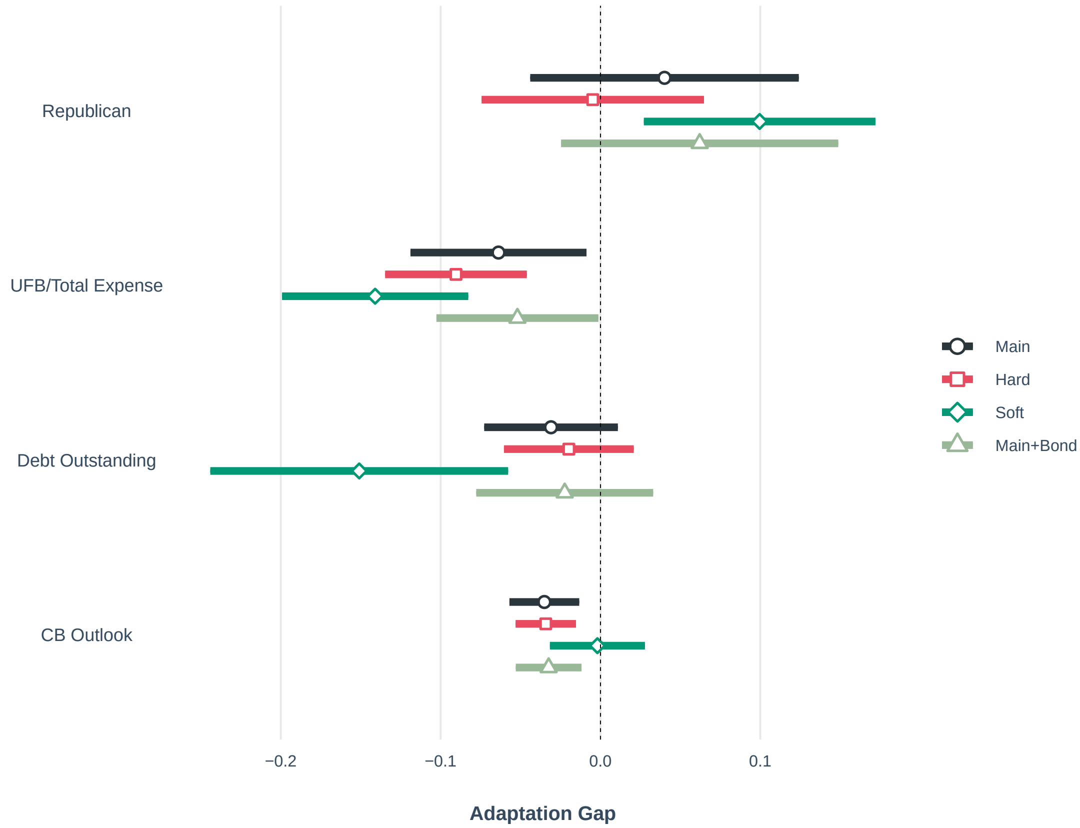
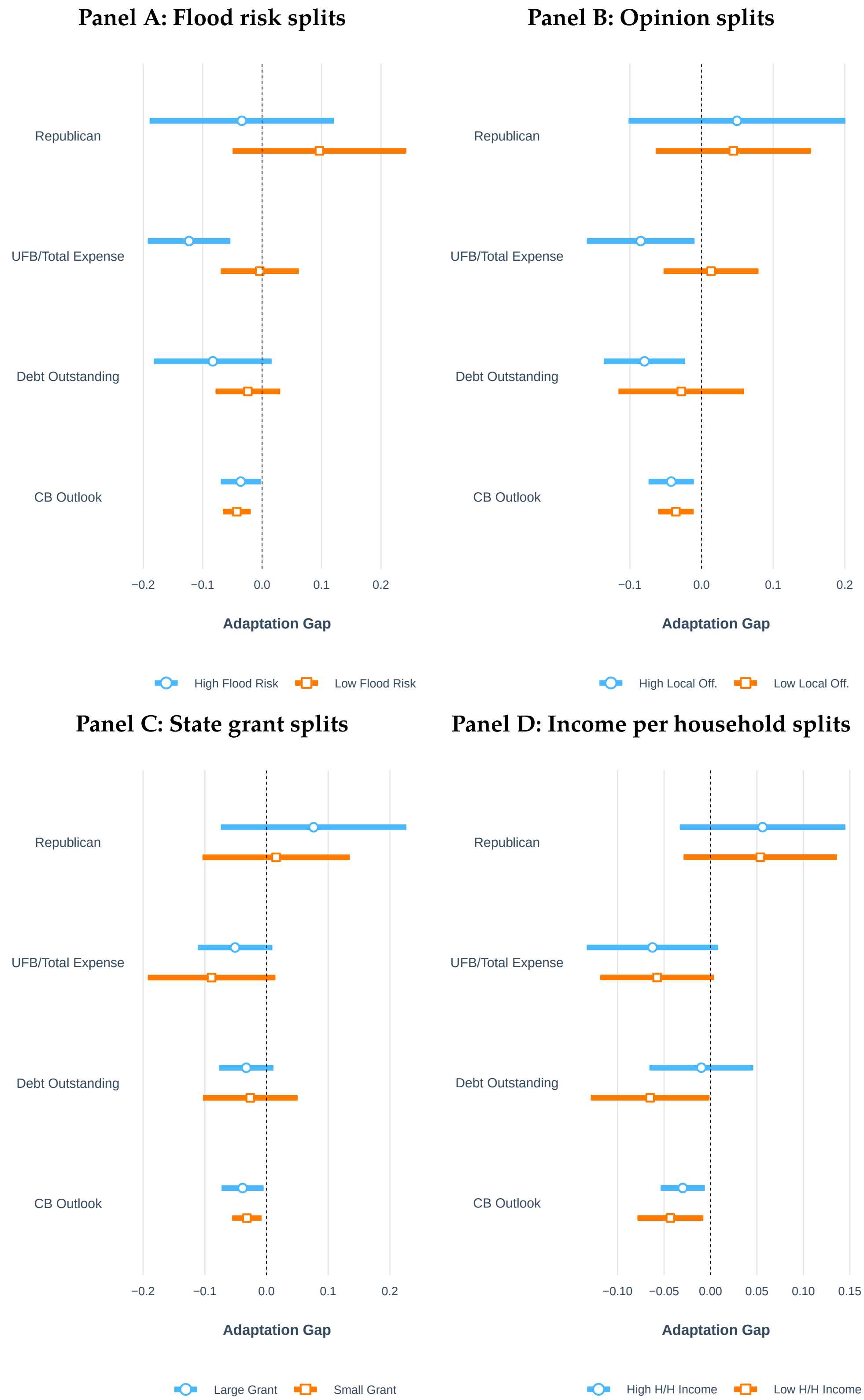


Figure 5: Determinants of adaptation gap.
This figure plots the estimates of the cross-sectional splits of eq. (2). Panel A shows splits by above-median within-state flood risk. Panel B presents the split by the results of the Yale Climate Opinion poll, where *High Local Off.* corresponds to the counties where a high percentage of respondents believe that local officials should do something about climate change, and *Low Local Off.* corresponds to the counties where this number is low. Panel C shows the results of the split between small and large amount of state grant. Panel D shows the results of the split by above-median household income. Bands indicate 95% confidence intervals. Full regression results are presented in Supplementary Table 5B.

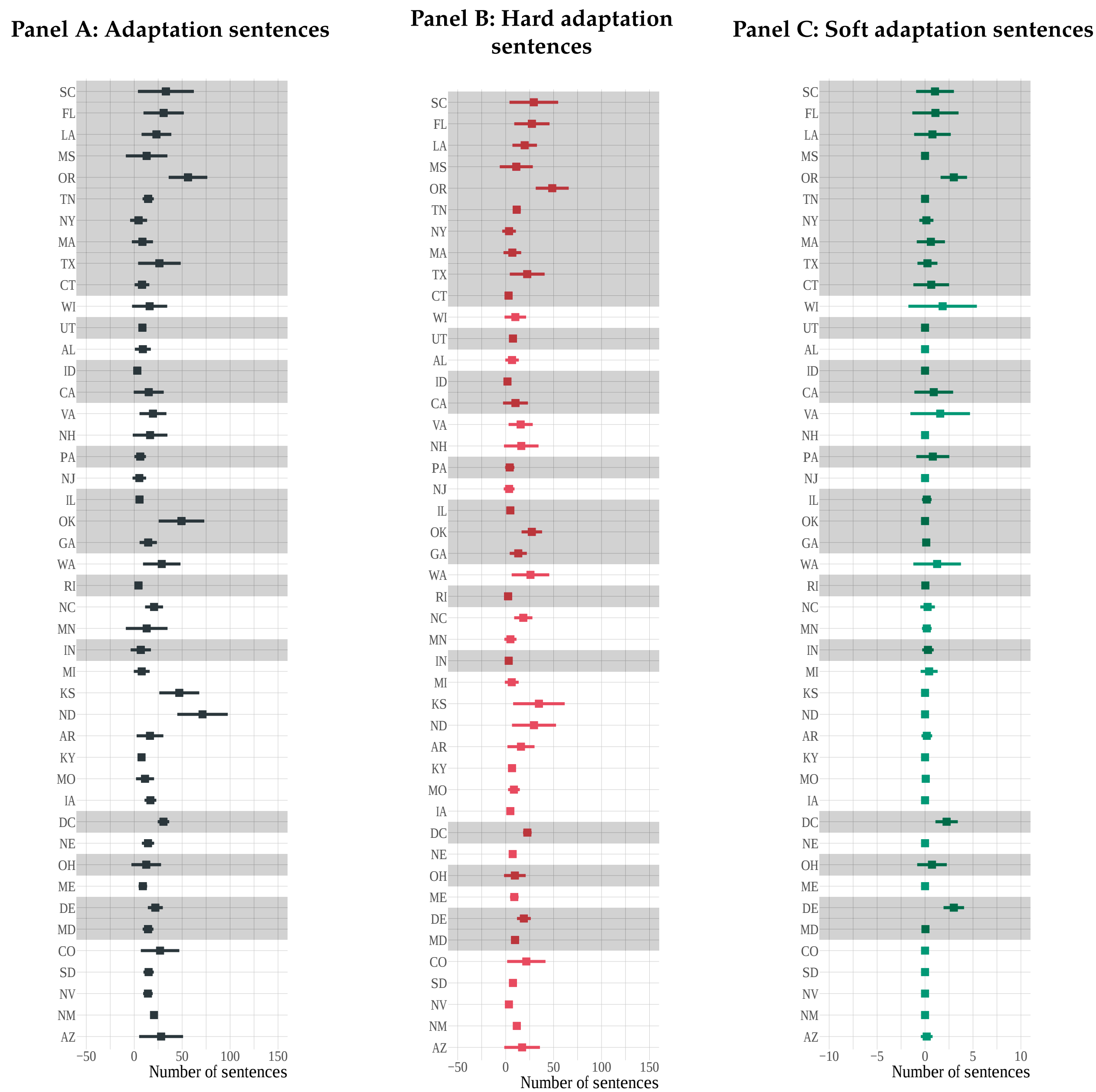


Supplementary tables and figures

New data highlights climate adaptation gap in cities with financial constraints and myopic planning horizons.

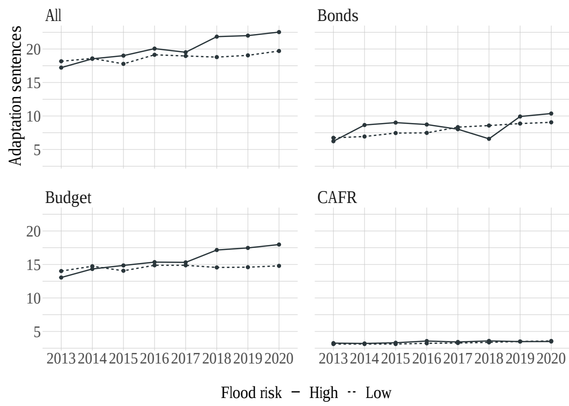
Supplementary Figure 1: State-level *adaptation*.

This figure summarizes adaptation measures across states. The points represent the mean number of sentences, while the bars represent the standard deviation. States on the vertical axis are ordered such that the percentage of properties with flood risk decreases from top to bottom. Panel A plots *main adaptation* measure. Panel B plots *hard adaptation*. Panel C plots *soft adaptation*.

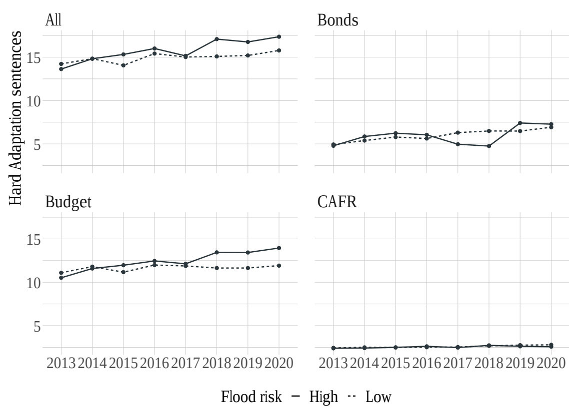


Supplementary Figure 2: ***Adaptation*** **over time and by flood risk.**
This figure presents *adaptation* in all documents, and budgets, CAFRs, and bond prospectuses separately over the sample period, 2013-2020. The solid line depicts the trends for high flood risk cities, and the dashed line shows the trends for low flood risk cities. High flood risk cities have above-top-quartile within-state percentage properties at risk, and low-flood risk cities have below-top-quartile percentage properties at risk. Panel A plots *main adaptation*. Panel B plots *hard adaptation*. Panel C plots *soft adaptation*.

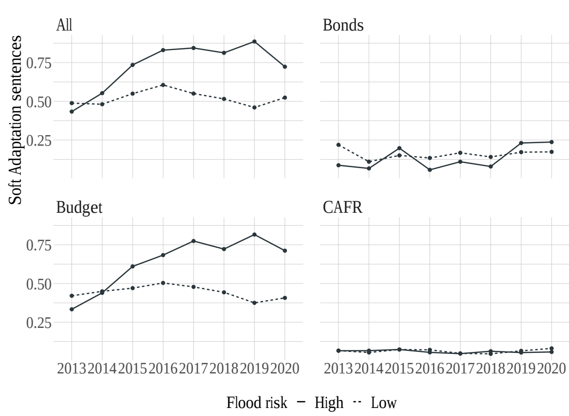
Panel A: Main Adaptation



Panel B: Hard Adaptation



Panel C: Soft Adaptation



Supplementary Table 1: Dictionary and illustration of our methodology.
The table reports the dictionary of the words used to create adaptation measures. Panel A reports the adaptation dictionary, separated into general words, hard adaptation words, and soft adaptation words. To construct our dictionary, we create an initial keywords dictionaries by examining relevant words used in the following documents: (i) the cities 2020 reporting guidance in the Carbon Disclosure Project ("CDP"), (ii) the city climate hazard taxonomy issued by the C40 Cities Climate Leadership Group, (iii) climate change summary for policymakers issued by the Intergovernmental Panel on Climate Change ("IPCC"), and (iv) climate change literature. We then augment the dictionaries by manually reading disclosures from sample cities over time (this list includes 9 cities in Massachusetts, 5 cities in Florida, and Washington, DC). This process allows us to capture words that cities use to describe adaptation actions but may not be commonly used in CDP, C40, IPCC guidance, and academic literature.

Panel A: Dictionary.

General	Hard Adaptation		Soft Adaptation
buyout program	breakwater	revetment	beach nourishment
buyout programs	bulkhead	revetments	beach restoration
erosion control	bulkheads	sandbag	bioswale
flood assistance	catch basin repair	sandbags	coral reef
flood control	detention storage systems	sea wall	dune barrier
flood management	dike	seawall	dune creation
flood mapping	dikes	spillway	earthen berm
flood mitigation	drain pipe	spillways	living shoreline
flood plain management	drainage channel	storm hardening	mangrove restoration
flood prevention	drainage evaluation	stormwater administration	marsh restoration
flood protection	drainage facilities	stormwater capture	mud flat
flood relief	drainage infrastructure	stormwater catch basin	mudflat
flood restoration	drainage line rehabilitation	stormwater collection	natural infrastructure solutions
hurricane preparedness	drainage mitigation	stormwater compliance	oyster reef
hurricane protection	drainage project	stormwater construction	rain garden
National Flood Insurance Program	drainage rehabilition	stormwater conveyance retrofit	rain gardens
prevention of flood	drainage replacement	stormwater drain	rainwater capture
sea level rise mitigation	drainage system	stormwater equipment	salt marsh
sea level rise modelling	drainage well	stormwater evaluation	sand replenishment
StormReady	drainpipe	stormwater improvement	shellfish reef
wind mitigation	dyke	stormwater infrastructure	shoreline conservation
wind resistance	dykes	stormwater inlet replacement	shoreline maintenance
wind retrofit	elevated roads	stormwater inspection	shoreline protection
flood preparedness	embankment	stormwater maintenance	shoreline stabilization
	embankments	stormwater master planning	soil retention
	exfiltration system	stormwater operation	tidal flat
	flood wall	stormwater pond	tidal marsh
	floodwall	stormwater project	tidal wetland
	groins	stormwater pump	wet detention basin
	ground water retention	stormwater pump station	wet pond
	groyne	stormwater quality improvement	wetland restoration
	groynes	stormwater retention	
	home elevation	stormwater retrofit	
	hurricane hardening	stormwater services	
	improv stormwater	stormwater system	
	improve drainage	stormwater vault	
	improve road drainage	stormwater vaults	
	inlets	street drainage	
	jetties	surface water maintenance	
	jetty	swale restoration	
	levee	tidal control valve	
	pervious pavement	tidal valves	
	project stormwater	water channel	
	pump system		
	raising streets		
	recharge wells		
	retention basin		
	retention pond		
	retention storage systems		

Supplementary Table 1: Dictionary and illustration of our methodology. Continued.
Panel B provides examples of the sentences with hard and soft adaptation. The keywords used to identify the passages are italicized.

Panel B: Examples of the paragraphs that contain adaptation-related senteces.

Textual Measure	Example Sentence	Source
Hard Adaptation	"This project provides for improvements to the Bermuda Boulevard *seawall* from 22nd Street to DeSoto Park and abutting City right-of-way."	Tampa, FL Budget 2018
Hard Adaptation	"Continued investment in the improvement of sewer and *stormwater infrastructure* reduces the need for emergency responses to sewer backups and flooding, saving on operating costs."	Cambridge, MA Budget 2018
Soft Adaptation	"Coordinated and permitted *beach nourishment* projects."	Galveston, TX Budget 2018
Soft Adaptation	"Prioritizing *natural infrastructure solutions* to sea level rise, such as citywide beach & dune system restoration, use of *bioswales* and tree plantings to mitigate stormwater runoff, as well as enhancement and expansion of *living shorelines*."	Miami Beach, FL Budget 2018

Supplementary Table 2: Sample composition by state.

This table provides descriptives of our sample cities. Sample comprises the cities with flood risk data from First Street Foundation, financial data from Muni Atlas, and the 2010 U.S. Census population of over 40,000 people for the states along the East and Gulf coast because these are states most prone to flood risk. For the remaining states, we collect data for cities with population above 150,000 people. This selection procedure yields 431 cities in 48 states and the District of Columbia for a period spanning 2013-2020. The table reports number of cities, *N Cities*, in each state; average city *Population* in a state; average percentage of *Properties at risk, %* in a state; number of collected budgets, *N Budgets*; number of collected CAFRs, *N CAFRs*; and number of collected bond prospectuses, *N Bond prospectuses*. *Total* sums up columns *N Cities*, *N Budgets*, *N CAFRs*, and *N Bond prospectuses* respectively; and provides averages of all the other variables. We obtained the collected documents by searching individual city websites, EMMA, Wayback Machine, and contacting city officials.

State	N Cities	Population	Properties at risk, %	Properties at risk, total	N Budgets	N CAFRs	N Bond prospectuses
AL	8	117,150	10.21	11,141	47	64	32
AR	6	82,137	5.76	3,222	30	35	14
AZ	13	300,493	0.81	836	104	104	61
CA	40	360,031	9.36	9,305	311	313	146
CO	3	447,221	3.66	7,606	24	24	17
CT	13	87,426	10.48	2,538	101	104	79
DC	1	602,723	5.30	7,300	8	8	8
DE	1	70,851	4.28	1,494	8	8	5
FL	54	116,732	24.22	16,646	414	420	155
GA	5	163,574	7.90	8,630	40	40	16
IA	1	203,433	5.32	5,291	8	8	8
ID	1	205,671	9.51	14,778	8	8	5
IL	3	1,015,456	8.47	29,926	23	23	20
IN	7	92,505	6.06	3,751	45	53	30
KS	3	205,983	6.04	7,516	19	20	19
KY	1	295,803	5.57	6,713	8	8	8
LA	8	133,648	20.54	14,626	60	60	25
MA	38	75,953	11.11	2,212	272	282	282
MD	3	249,136	4.03	6,527	23	24	18
ME	1	66,194	4.86	1,511	8	8	8
MI	10	151,824	6.02	5,173	68	74	51
MN	8	133,970	6.40	3,606	60	64	46
MO	7	173,944	5.42	6,863	55	56	40
MS	4	82,838	19.42	7,747	25	28	20
NC	19	159,566	6.36	6,054	146	147	63
ND	2	79,194	5.72	1,532	16	16	16
NE	2	333,668	4.99	7,338	13	16	15
NH	3	79,585	9.46	2,095	18	24	18
NJ	10	115,507	8.49	2,611	69	68	54
NM	1	545,852	1.41	3,319	8	8	8
NV	5	274,786	3.10	3,227	40	40	23
NY	15	639,853	13.36	10,087	111	103	100
OH	10	225,230	4.86	7,590	69	78	50
OK	2	485,952	7.20	21,558	11	13	16
OR	3	298,199	17.29	21,945	21	23	13
PA	12	207,085	8.67	7,628	93	92	49
RI	4	95,572	7.01	3,582	30	32	14
SC	7	82,333	24.50	12,658	51	54	25
SD	1	153,888	3.43	2,192	7	5	4
TN	3	331,146	14.20	22,404	24	24	11
TX	65	203,780	10.76	10,744	512	517	433
UT	1	186,440	10.37	10,612	8	8	8
VA	15	139,741	8.96	5,621	117	120	88
WA	9	169,295	7.29	10,539	71	69	36
WI	3	293,121	10.52	7,391	24	24	24
Total	431	234,100	8.64	8,126	3,228	3,317	2,181

Supplementary Table 3: Summary statistics.
This table presents summary statistics for *adaptation* and the city-specific characteristics. *Main Adaptation* is the number of adaptation sentences across document types. *Budget Adaptation, CAFR Adaptation, Bonds Adaptation* is the number of adaptation sentences in budgets, CAFR, and bond prospectuses. *Hard Adaptation* and *Soft Adaptation* is the number of adaptation sentences corresponding to hard and soft adaptation, respectively. *Capital Budget Outlook* is the number of years in the capital budget, as reported. *Population* is the total population of the city. *Total Debt per Capita* is the total debt outstanding, scaled by *Population*. *UFB/Total Expense* is unrestricted fund balance scaled by total expenses. *Fund Expense per Capita* is per capita expenses from the city funds that are related to capital projects and emergency preparedness. *CRS Class Code* indicates whether cities are eligible for the higher flood insurance discount from CRS (Community Rating System), an incentive program that allows cities with higher flood preparedness can receive a higher flood insurance discount. *CRS Class Code* decreases in preparedness, with a class code of 1 representing the highest level of preparedness with an insurance discount of 45%, whereas a class code of 10 represents the lowest level of preparedness with no insurance discount. *Large Grant* is an indicator for above-average amount of the *State Grant*, the highest monetary amount of state grant a city can apply for climate adaptation. *High Local Officials* is an indicator of an above-average percentage of the respondents to the Yale Climate Opinion survey who believe that local officials can do more to address global warming.

Panel A: Descriptive statistics.

Variable	N	Mean	SD	p25	p50	p75
Main Adaptation	3,161	19.18	19.58	5.00	13.00	26.00
Hard Adaptation	3,161	15.20	16.57	3.00	10.00	21.00
Soft Adaptation	3,161	0.58	1.67	0.00	0.00	0.00
Budget Adaptation	3,161	15.08	17.32	3.00	9.00	21.00
CAFR Adaptation	3,161	3.43	4.00	1.00	2.00	5.00
Main+Bonds Adaptation	2,011	28.40	28.55	8.00	20.00	37.00
Bonds Adaptation	2,011	8.33	13.29	1.00	4.00	9.00
Total Sentences	3,161	4,873.16	9,115.51	2,380.00	3,620.00	5,267.00
Capital Budget Outlook	2,902	4.07	2.20	1.00	5.00	5.00
Population	3,161	220,144.32	524,086.41	61,769.00	101,749.00	205,228.00
Flood Risk	3,161	11.18	11.76	4.83	7.59	12.73
Total Debt per Capita	3,119	1,770.01	1,766.20	754.28	1,349.43	2,213.09
UFB/Total Expense	2,897	-0.45	0.84	-0.88	-0.26	0.14
Fund Expense per Capita	753	315.86	446.79	103.60	194.55	359.34
CRS Class Code	2,014	6.95	1.51	6.00	7.00	8.00
Large Grant	3,161	0.53	0.50	0.00	1.00	1.00
High Local Officials	3,161	0.51	0.50	0.00	1.00	1.00
High H/H Income	3,090	0.50	0.50	0.00	0.50	1.00

Panel B: Descriptive statistics - party affiliation.

N	Democrat	Republican	Other
3,161	1,463	821	877

Supplementary Table 3: Summary statistics. Continued.

Panel C: Univariate correlations

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
[1] Main	1.00															
[2] Hard	0.94	1.00														
[3] Soft	0.33	0.28	1.00													
[4] Budget	0.96	0.92	0.35	1.00												
[5] CAFR	0.56	0.50	0.15	0.39	1.00											
[6] Main+Bonds	0.34	0.29	0.13	0.27	0.50	1.00										
[7] Flood Risk	0.21	0.24	0.26	0.20	0.19	0.09	1.00									
[8] Capital Budget Outlook	0.24	0.21	0.11	0.25	0.08	0.06	-0.02	1.00								
[9] Population	0.13	0.11	0.06	0.11	0.13	0.27	-0.08	0.03	1.00							
[10] Total Debt per Capita	-0.03	-0.05	0.04	-0.02	-0.04	0.13	-0.05	0.07	0.17	1.00						
[11] UFB/Total Expense	0.13	0.15	-0.02	0.11	0.16	0.01	-0.00	0.12	-0.21	-0.19	1.00					
[12] Fund Expense per Capita	0.03	-0.01	0.12	0.01	0.15	0.22	0.25	-0.02	0.08	0.26	0.02	1.00				
[13] CRS Class Code	-0.28	-0.25	-0.09	-0.27	-0.19	-0.23	-0.12	-0.09	-0.02	0.02	-0.09	0.02	1.00			
[14] Large Grant	-0.10	-0.07	0.03	-0.09	-0.06	-0.05	0.13	-0.02	-0.07	-0.02	-0.23	0.05	0.03	1.00		
[15] High Local Officials	0.03	0.02	-0.05	0.02	0.02	-0.06	-0.10	0.01	-0.13	0.01	0.10	0.05	-0.04	-0.05	1.00	
[16] High H/H Income	0.12	0.10	0.08	0.12	0.06	0.06	-0.08	0.09	0.10	0.08	0.08	0.03	-0.07	-0.16	-0.10	1.00

Supplementary Table 4: Determinants: Flood risk.
Panel A presents the association between flood risk and *adaptation*. The dependent variables are *main adaptation* (column (1)), *hard adaptation* (column (2)), and *soft adaptation* (column (3)). Column (4) presents the same specification as column (1) but uses the *main+bond adaptation* that incorporates bond prospectus data. *Flood Risk* is the percentage of properties at risk in a city. *Log*(*Population*) is a natural logarithm of population. *Log*(*N Sentences*) is the natural logarithm of the total number of sentences in city-level documents. We also include state and year fixed effects. Standard errors are clustered at the state level. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: Adaptation and Flood Risk

	Dependent variable:			
	Adapt	Hard Adapt	Soft Adapt	Adapt
	(1)	(2)	(3)	(4)
Flood Risk	0.01^{***}	0.01^{***}	0.02^{***}	0.01^{**}
	(4.17)	(2.92)	(6.11)	(2.53)
Log(Population)	−0.01	−0.02	0.04^{**}	0.05
	(−0.09)	(−0.38)	(2.66)	(0.77)
Log(N Sentences)	0.77^{***}	0.75^{***}	0.15^{***}	0.65^{***}
	(9.37)	(9.30)	(3.32)	(8.25)
Measure	Main	Main	Main	Main+Bonds
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered s.e.	State	State	State	State
Observations	3,161	3,161	1,373	2,011
Adjusted R^2	0.56	0.58	0.27	0.53

Supplementary Table 4: Determinants: Flood risk. Continued.
Panel B presents difference-in-difference regressions relative to extreme hurracaines. The dependent variables are *main adaptation* (column (1)), *hard adaptation* (column (2)), and *soft adaptation* (column (3)). Column (4) presents the same specification as column (1) but uses the *main+bond andaptation* that incorporates bond prospectus data. *High Flood Risk* cities have top-quartile percentage properties at risk. *Log*(*Population*) is a natural logarithm of population. *Post* is an indicator variable equal to one after an extreme weather event. *Log*(*N Sentences*) is the natural logarithm of the total number of sentences in city-level documents. We also include state-year fixed effects. Standard errors are clustered at the state level. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel B: Adaptation after Hurricanes.

	Dependent variable:			
	Adapt	Hard Adapt	Soft Adapt	Adapt
	(1)	(2)	(3)	(4)
High Flood Risk × Post	0.20^{**}	0.23^{**}	0.14^{**}	0.19^{**}
	(2.15)	(2.61)	(2.37)	(2.13)
High Flood Risk	−0.03	−0.08	0.11^{**}	0.01
	(−0.36)	(−1.03)	(2.41)	(0.19)
Log(Population)	−0.01	−0.03	0.01	0.04
	(−0.24)	(−0.59)	(0.82)	(0.56)
Log(N Sentences)	0.77^{***}	0.75^{***}	0.16^{***}	0.67^{***}
	(9.31)	(9.28)	(3.80)	(8.37)
Measure	Main	Main	Main	Main+Bonds
State-Year FE	Yes	Yes	Yes	Yes
Clustered s.e.	State	State	State	State
Observations	3,161	3,161	1,373	2,011
Adjusted R^2	0.52	0.55	0.12	0.49

Supplementary Table 5: Determinants: Adaptation gap.
Panel A presents the relationship between city-level characteristics and *Adapt Gap*, an indicator that equals to one if the residuals from the Supplementary Table 4A regressions are negative. The column specifications correspond to adaptation gaps estimated using *main adaptation* (column (1)), *hard adaptation* (column (2)), and *soft adaptation* (column (3)). Column (4) presents the same specification as column (1) but uses the adaptation gap derived from a measure that incorporates bond prospectus data. *Republican* is an indicator variable equal to one if the city has a Republican mayor. *UFB/Total Expense* is unrestricted fund balance scaled by total expenses. *Total Debt per Capita* is total debt outstanding scaled by the population of the city. *Capital Budget Outlook* is the reported number of years in the capital budget. We also include state and year fixed effects. Standard errors are clustered at the state level. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: Adaptation Gap

	Dependent variable:			
	Adapt Gap	Hard Adapt Gap	Soft Adapt Gap	Adapt Gap
	(1)	(2)	(3)	(4)
Republican	0.04	−0.005	0.10**	0.06
	(0.96)	(−0.14)	(3.06)	(1.45)
UFB/Total Expense	−0.06**	−0.09***	−0.14***	−0.05**
	(−2.34)	(−4.12)	(−5.39)	(−2.07)
Log(Total Debt per Capita)	−0.03	−0.02	−0.15***	−0.02
	(−1.49)	(−0.98)	(−3.61)	(−0.82)
Capital Budget Outlook	−0.04***	−0.03***	−0.002	−0.03***
	(−3.25)	(−3.66)	(−0.14)	(−3.18)
Measure	Main	Main	Main	Main+Bonds
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered s.e.	State	State	State	State
Observations	2,614	2,614	1,168	1,751
Adjusted R^2	0.04	0.05	0.09	0.03

Supplementary Table 5: Determinants: Adaptation gap. Continued.
Panel B presents cross-sectional splits of the associations between city-level characteristics and *Adapt Gap*, an indicator that equals to one if the residuals from the Supplementary Table 4A regressions are negative. Columns (1) and (2) split the sample by the median within-state flood risk. Columns (3) and (4) split the sample by the percentage of respondents who believe local officials should do something about climate change, taken from the Yale Climate Opinion poll. Columns (5) and (6) split the sample by the median monetary amount of state grants on adaptation. Columns (7) and (8) show the results of the split by above-median household income. We also include state and year fixed effects. Standard errors are clustered at the state level. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel B: Adaptation Gap

	Dependent variable:							
	Adapt Gap							
	High Flood Risk	Low Flood Risk	High Local Off.	Low Local Off.	Large Grant	Small Grant	High H/H Income	Low H/H Income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Republican	−0.03	0.10	0.05	0.04	0.08	0.02	0.06	0.05
	(−0.44)	(1.34)	(0.67)	(0.83)	(1.06)	(0.27)	(1.06)	(1.10)
UFB/Total Expense	−0.12***	−0.004	−0.09**	0.01	−0.05*	−0.09*	−0.06	−0.06
	(−3.57)	(−0.12)	(−2.31)	(0.40)	(−1.76)	(−1.80)	(−1.49)	(−1.58)
Log(Total Debt per Capita)	−0.08*	−0.02	−0.08***	−0.03	−0.03	−0.03	−0.01	−0.06*
	(−1.69)	(−0.90)	(−2.86)	(−0.65)	(−1.55)	(−0.71)	(−0.30)	(−1.71)
Capital Budget Outlook	−0.04**	−0.04***	−0.04**	−0.04***	−0.04**	−0.03**	−0.03**	−0.04**
	(−2.17)	(−3.71)	(−2.74)	(−2.92)	(−2.37)	(−2.79)	(−2.12)	(−2.05)
Measure	Main	Main	Main	Main	Main	Main	Main	Main
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered s.e.	State	State	State	State	State	State	State	State
Observations	1,352	1,262	1,316	1,298	1,337	1,277	1,396	1,189
Adjusted R^2	0.10	0.12	0.12	0.07	0.05	0.02	0.05	0.11

For Online Publication

New data highlights climate adaptation gap in cities with financial constraint and myopic planning horizons.

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Appendix A: Dictionary verification.

Following Li et al. (2020), we use single-word unigrams and two-word bigrams to form a hybrid dictionary. The unigrams capture keywords that are unambiguously related to climate disclosure (e.g., levee), while the bigrams capture keywords that would pick up irrelevant sentences without the presence of a second clarifying word.

To validate that none of our unigrams are irrelevant, we extract all of the bigrams that contain a given unigram, and then manually examine the most frequent bigrams. If only a few bigrams are irrelevant, we retain the unigram in the keyword list and exclude all the irrelevant bigrams. An example is the unigram "seawall." Most references to seawall are correctly referencing the hard adaptation infrastructure, except for the bigram "seawall parking" which refers to parking lot around the seawall. Thus, we exclude the bigram "seawall parking" from the keywords list. However, in some cases, when the majority of unigram uses are irrelevant or misleading, we drop the unigram but add the relevant bigrams to our keywords list. An example is the unigram "stormwater," which can appear over a thousand times in a single document, but mostly refers to stormwater utility, system, or a fund. In such cases, we drop the unigram and retain relevant bigrams, such as "stormwater improvement." The most frequent bigrams are presented in the **Table A1**.

We also conduct a thorough manual review of words that appear frequently in our financial disclosures. Specifically, we closely examine any keyword that appears more than 100 times in a single document, as well as any keyword that has more than 0.5 occurrences in an average document (these keywords are commonly present such that each shows up on average once in every other document). During this process, we update our list if we find any keywords that are frequently used in irrelevant phrases and sentences. In some cases, we retain an unstemmed keyword if the stemmed version is too general. For example, we keep the full word "levee" because the stemmed version "leve" picks up irrelevant words such as "lever." For unstemmed keywords, we include multiple versions of the keywords, such as ''dike" and ''dikes". We repeat this process multiple times to finalize our dictionary. The current list of keywords can be found in **Table 2A**. **Table 2B** provides examples of sentences that contain words from the hard and soft adaptation dictionaries.

Table A1: Relative frequency of adaptation words.
The table reports the relative frequency of the keywords used to create climate adaptation measures.

Keyword	Frequency	Keyword	Frequency	Keyword	Frequency
flood control	13,245	dikes	321	flood assist	51
drainag system	13,031	beach nourishment	304	wind retrofit	43
seawal	6,779	breakwater	289	wind resist	40
stormwat system	6,527	wetland restor	283	exfiltr system	38
drainag project	6,371	sea wall	280	surfac water mainten	38
street drainag	6,177	stormwat inspect	262	improv road drainag	35
inlet	5,305	flood prevent	257	sea level rise mitig	35
stormwat improv	4,179	shorelin stabil	250	sandbag	34
eros control	3,468	stormwat retent	242	tidal wetland	34
stormwat project	3,274	retention pond	241	marsh restor	33
drainag facil	3,079	retention basin	238	stormready	32
stormwat infrastructur	3,078	flood wall	223	earthen berm	31
flood protect	3,074	jetty	223	home elev	31
stormwat servic	2,831	salt marsh	203	drainag evalu	30
stormwat oper	2,723	stormwat equip	186	tidal marsh	30
improv drainag	2,576	sand replenishment	173	stormwater vault	24
levee	2,494	hurrican prepared	170	flood restor	21
stormwat mainten	2,349	embankments	167	shorelin mainten	19
flood mitig	1,967	recharg well	165	rainwat captur	14
drainag infrastructur	1,798	rain garden	158	flood prepared	14
improv stormwat	1,734	drainag rehabilit	155	elev road	13
bulkhead	1,511	live shorelin	155	groins	11
project stormwat	1,261	jetties	149	oyster reef	11
drainag channel	1,074	wet pond	140	revetments	10
stormwat master plan	971	shorelin protect	131	tidal control valv	8
spillway	970	revetment	124	drainag line rehabilit	6
flood relief	947	stormwat drain	121	natur infrastructur solut	6
pump system	909	hurrican protect	120	ground water retent	5
dike	891	dyke	114	mudflat	5
stormwat pump	873	buyout program	113	detent storag system	4
stormwat collect	851	dykes	112	stormwat evalu	4
drain pipe	833	drainag replac	106	stormwat inlet replac	4
national flood insurance program	769	drainag well	98	mud flat	4
stormwat pump station	686	water channel	96	sea level rise model	3
stormwat pond	623	stormwat captur	89	shorelin conserv	3
embankment	614	drainpip	86	buyout programs	2
flood manag	510	stormwater vaults	85	stormwat convey retrofit	2
floodwal	496	spillways	81	mangrov restor	1
rain gardens	496	sandbags	73		
flood map	455	stormwat qualiti improv	72		
stormwat complianc	455	swale restor	72		
bulkheads	446	wind mitig	71		
catch basin repair	438	hurricane hardening	69		
beach restor	436	prevent of flood	65		
stormwat administr	418	pervious pavement	62		
flood plain manag	403	rais street	62		
stormwat construct	398	stormwat catch basin	62		
bioswal	395	storm hardening	58		
drainag mitig	392	tidal valv	53		
stormwat retrofit	371	coral reef	52		

Appendix B: Validating *adaptation*.

We take three steps to validate that our adaptation measures pick up meaningful variation in a city's climate adaptation. First, we examine if cities with higher *adaptation* have higher expenses on funds that relate to adaptation. Second, we test if higher *adaptation* is associated with a lower flood insurance premium through a FEMA program. Third, we study the market pricing of climate risks and adaptation in the municipal bonds market and examine if *adaptation* is associated with a lower bond yield.

Fund expense

Our first validation test examines the relationship between *adaptation* and cities' spending on infrastructure to reduce flood risks. To run this analysis, we make use of the institutional feature of municipal financial reporting that requires cities to separately report financial information at the fund level. Each fund is assigned to a different purpose that is material to the city (e.g., utilities, water, pensions, etc.). A positive correlation between *adaptation* and expenses from the relevant capital project and emergency funds would indicate that our measure captures adaptation efforts.

The fund-level data is largely unavailable, but Muni Atlas provides this data for a short period starting in 2017. The names and purposes of the funds are not standardized and can vary across cities. We manually identify the funds related to capital projects, capital improvements, disaster relief, and flood-related emergencies. We then aggregate the total expenditures from these funds at the city-year level. Because of the limited number of cities with relevant fund expenses, and because the Muni Atlas fund-level data starts in 2017, the sample size drops to 753 observations. To ensure comparability across cities, we scale the fund expenses by city population and take the natural logarithm transformation of the variable to make sure it is similar to the normal distribution.

Table B1 Panel A regresses our textual measures on $Log(Fund\ Expense\ per\ Capita)$. Since the distribution of *adaptation* measures is skewed, we use their natural logarithm transformations in the regressions. To account for the different city sizes, we include the natural logarithm of the population as a control variable. We also control for the natural logarithm of the total number of sentences because cities with more resources may prepare longer financial documents. We include city and year-fixed effects and cluster standard errors by city.

Columns (1)-(3) report the results for our *main* measures of adaptation, which are based on budgets and annual reports. Column (1) shows the results for the aggregate measure, Column (2) shows the results for the *hard adaptation* measure, and Column (3) shows the results for the *soft adaptation* measure, which is restricted to coastal cities as they are the only cities that can engage in soft adaptation. Column (4) reports the results for *main+bond* measure, which is based on budgets, annual reports, and bond prospectuses. The coefficient on the fund expense is positive and statistically significant for all our adaptation measures, which supports our intuition that adaptation sentences are picking up meaningful variation of the underlying construct.

Flood insurance

Next, we document that our measure is correlated with a lower flood insurance premium by using data from the Community Rating System (CRS). CRS is a voluntary system where cities with higher flood preparedness can receive a higher flood insurance discount from the National Flood Insurance Program ("NFIP'') (42). NFIP is the flood insurance managed by the FEMA, and participation is required for Special Flood Hazard Areas, which are areas exposed to a 1% or greater risk of flooding in any given year.[1] Cities that participate in the CRS will receive a code, ranging from 1 to 10, with a lower number indicating a higher level of preparedness. For example, a CRS code of 1 means the highest level of preparedness and a 45% insurance discount, while a code of 10 means the lowest level of preparedness and no insurance discount.

To participate in CRS, cities need to provide documentation that demonstrates the city is implementing activities that lower potential flood damage, such as activities in floodplain management planning, flood protection, and drainage system maintenance. Cities that take more steps to adapt to floods will have lower CRS scores. If our measures accurately capture a city's actions to adapt to floods, it will be negatively correlated with their CRS scores.

Table B1 Panel B regresses our *main adaptation* measures on the CRS class code and a set of control variables described above. We include state fixed effects instead of city fixed effects because we observe in the data that once the city participates, it remains in CRS. The coefficient on CRS is negative and statistically significant for *main* and *hard adaptation*. This result provides support that higher *adaptation* captures cities that are more

[1] As of 2022, over 1,500 communities participated in CRS.

prepared for flood risk, and as a result, receive a lower insurance premium. However, the coefficient on *soft adaptation* is not statistically significant, which suggests that the CRS may not assign equal weight to soft adaptation compared to hard adaptation. It is possible that the lack of statistical significance for the *soft adaptation* measure in our analysis is explained by lower power due to the smaller sample size of coastal cities used in the regression.

Market pricing of climate risks

As a third validation test, we examine whether our textual measures of adaptation are priced in the municipal bonds market. Prior research finds evidence that local governments more exposed to the sea level rise face a higher cost of financing (19, 20).[2] If our measure captures cities' preparedness against climate risks, it will provide incremental information about climate risks that would be incorporated in municipal bonds' prices. Specifically, we expect higher *adaptation* to be correlated with a lower bond yield, particularly in areas that are at a higher risk of flooding.

We first replicate the key findings from previous studies by (23) and (24). We then expand on this by analyzing the interaction of adaptation and flood risk to specifically examine the impact of adaptation in areas that are more prone to flooding. We run the following regressions:

$$\begin{aligned} Spread_{i,t} = {} & \beta_1 Flood\,Risk_i + \beta_2 Adaptation_{i,t} + \beta_3 Flood\,Risk_i \times Adaptation_{i,t} \\ & + \beta_4 X_{i,t} + Fixed\,Effects_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where *Spread*$_{i,t}$ is the offering (or secondary) spread for bonds issued by municipality i at time t, $ *Spread*_{i,t}$ is defined as the difference between the bond yield and the maturity-matched yield from the Municipal Market Advisors (MMA) curve. *Flood Risk*$_i$ is the flood risk measure from the First Street Foundation. In these analyses, we use our *main+bond* adaptation measure which includes the data from bond prospectuses since market participants are likely to incorporate this information in their decision-making. Because adaptation measures are independent variables in this regression, we scale *adaptation* by the total number of sentences to ensure comparability across cities. To be able to compare the mitigating effect of adaptation on flood risk numerically, we standardize both *Flood Risk*$_i$ and *Adaptation*$_{i,t}$. Finally, $X_{i,t}$ is a vector of controls from and $Fixed\,Effects_{i,t}$ is the fixed effects structure specified in (23) and (24). We restrict the sample to before 2020 to avoid confounding by a number of unusual events that happened in the municipal market that year (44).

Our main coefficient of interest is the interaction coefficient β_3, which we expect to be negative. While cities with higher flood risk exposure have higher borrowing costs (as documented in previous research), cities that have implemented strong adaptation measures to address these risks may be able to reduce these costs by reducing the overall level of risk.

Table B1 Panel C reports the results. Columns (1)-(5) test our *adaptation* measures in the primary municipal bond market following (23).[3] In Column (1) we replicate the main result of (23) which shows that flood risk is priced in the primary offering market (the coefficient on $Flood\,Risk_i$ is positive and statistically significant).[4] Column (2) adds the interaction of $Flood\,Risk_i$ and $Adaptation_{i,t}$ to identify the mitigating effect of adaptation actions on the offering bond yields. Column (3) includes city fixed effects that absorb the mean level of offering yield spreads at the city level. This is our primary specification in subsequent analyses.

The coefficients estimates of β_3 are negative and statistically significant in all specifications. In terms of economic magnitude, Column (2) indicates that while one standard deviation increase in flood risk is associated with 2.9 bp increase in offering yield, a one standard deviation increase in $Adaptation_{i,t}$ mitigates this effect by reducing the offering yield spreads by 0.75 bp, a substantial decrease in economic terms.

[2]These papers measure climate risk-based mostly on geomorphological information. (23) uses a measure of climate risk from (43), which estimates the impact of the rise in sea level using adaptation assumptions that are partly based on author estimates. (43) acknowledge that their defense level is based on limited information, and they call for more research to improve the measure. (24) use sea level rise exposures from the National Oceanic and Atmospheric Administration ("NOAA"), which captures the locations that will be inundated following an increase in average sea level, assuming the city has not adopted any adaptation measures.

[3]Note that the number of bond observations in this analysis exceeds the number of bond prospectuses collected (see **Table 2**). This is because each municipal bond issue has multiple bonds and only one bond prospectus.

[4]Following (23), we include controls for the log of the issue size, the log of the maximum maturity, the bond's initial credit rating, the log of the number of CUSIPS packaged in the same issue, the log of the number of underwriter deals that the bond's underwriter has issued in the sample, and indicator variables for whether the bond is callable, insured, sinkable, pre-refunded, funded by general obligation, competitively issued, federally tax-exempt, state tax-exempt, or subject to AMT. Just like in (23), we include state-year fixed effects and cluster standard errors by county.

Once we include the city fixed effects in Column (3), the adaptation effect becomes stronger, with one standard deviation increase in adaptation corresponding to -2.8 bp mitigating effect in municipal credit spreads. Compared to an average spread of 40 bp, this coefficient suggests that one standard deviation in adaptation results in 7.25% decrease in municipal bond spreads. Most of the effect is related to *hard* $adaptation_{i,t}$, where one standard deviation increase in the measure implies to 2.6 bp decrease in municipal spread (Column (4)). The corresponding change in *soft* $adaptation_{i,t}$ decreases spreads by 0.5 bp, as shown in Column (5).

Columns (6)-(10) of the **Table B1 Panel C** report the secondary market test results.[5] Just like with the primary market analyses, we first replicate (24) in Column (6), and then include the interaction $Flood\,Risk_i$ and $adaptation_{i,t}$ in Column (7), and city-level fixed effects in Columns (8)-(10). The coefficients range from -1.2 to -1.8 across the last three columns, implying that one standard deviation increase in adaptation corresponds to a 1.2 bp to 1.8 bp decrease in municipal credit spreads. Compared to the average secondary spread of 12.8 bp, these estimates are economically meaningful. Overall, the results of the market tests are consistent with cities with higher *adaptation* being perceived as less risky by the municipal market.

Robustness and placebo analyses

To further confirm the validity of our measures, we conduct robustness analyses with different definitions *adaptation* and a falsification analysis with a placebo measure unrelated to climate risks.

As shown in **Figure 1**, words related to stormwater and drainage constitute the majority of the most common adaptation words. Although stormwater and drainage systems are critical adaptation strategies, nearly all cities have such systems to protect against regular rain. This raises concerns that we may be capturing normal city infrastructure rather than climate adaptation efforts. To address these concerns, we create three alternative measures of adaptation: (1) *adapt-drain*, which excludes all drainage-related words from our main measure, (2) *adapt-stormwater*, which subtracts stormwater-related words from our main measure, and (3) *adapt-drain-stormwater*, which excludes both drainage and stormwater-related words from our main measure. Online Appendix **Table B2** presents estimates for our three sets of validation tests using dependent variables that exclude drainage and stormwater words. These regressions indicate that our alternative textual measures are still correlated with city-level adaptation efforts, suggesting that these associations are not solely driven by sentences containing drainage and stormwater words.

We also conduct a falsification analysis with a placebo measure that is unrelated to climate risks. If the placebo measure better fits the data, it could indicate that the relationship between our adaptation measures and the validating dependent variables is due to misspecification and that our measures are capturing unobservable characteristics of financial disclosures instead of adaptation efforts.

For the placebo analysis, we choose a topic that is orthogonal to adaptation and construct a measure that captures the number of sentences related to police and general safety. We repeat our validation tests using this safety/police measure. The results, reported in the Online Appendix **Table B3**, show that placebo is not associated with any of the validation proxies, providing support for the construct validity of our measures.

[5]Following (24), we include controls for the log of the bond's time to maturity, callability, and insured status interacted with the year, city-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. Just like in (24), we include trade-month fixed effects and cluster standard errors by county and year-month.

Table B1: Validation of textual measures.
This table presents validation regressions of our adaptation measures. Panel A presents the association between our measures and *Log*(*Fund Expense per Capita*), natural logarithm of total expenses from the city funds that are related to capital projects and emergency preparedness, scaled by city population. The dependent variables are *adaptation* (column (1)), *hard adaptation* (column (2)), and *soft adaptation* (column (3)). Column (4) presents the same specification as column (1) but uses the *main+bond* measure that incorporates bond prospectus data. We control for the *Log*(*Population*), the natural logarithm of city-level population and *Log*(*N Sentences*), natural logarithm of the total number of sentences in city-level documents. We also include city and year fixed effects. Standard errors are clustered at the city level. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively. The number of observations in Panel A drops because Muni Atlas only has fund-level data for 2017-2020.

Panel A: Validation: adaptation and fund expenses.

	Dependent variable:			
	Adapt	Hard Adapt	Soft Adapt	Adapt
	(1)	(2)	(3)	(4)
Log(Fund Expense per Capita)	0.07^{**}	0.06^{**}	0.05^{*}	0.07^{*}
	(2.46)	(2.00)	(1.86)	(1.86)
Log(Population)	0.15	-0.21	0.13	-0.27
	(0.23)	(-0.31)	(0.19)	(-0.37)
Log(N Sentences)	0.60^{***}	0.51^{***}	0.14	0.53^{***}
	(4.43)	(4.43)	(1.45)	(7.74)
Measure	Main	Main	Main	Main+Bonds
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered s.e.	City	City	City	City
Observations	753	753	336	483
Adjusted R^2	0.93	0.93	0.80	0.92

Table B1: Validation of textual measures, continued.
Panel B presents the association between *adaptation* and the Community Rating System (CRS) class code. *CRS Class Code* indicates whether cities are eligible for the higher flood insurance discount from CRS (Community Rating System), an incentive program that allows cities with higher flood preparedness to receive a higher flood insurance discount. *CRS Class Code* decreases in preparedness, with a class code of 1 representing the highest level of preparedness with an insurance discount of 45%, whereas a class code of 10 represents the lowest level of preparedness with no insurance discount. The dependent variables are *adaptation* (column (1)), *hard adaptation* (column (2)), and *soft adaptation* (column (3)). Column (4) presents the same specification as column (1) but uses the *main+bond* measure that incorporates bond prospectus data. We control for the *Log*(*Population*), the natural logarithm of city-level population and *Log*(*N Sentences*), natural logarithm of the total number of sentences in city-level documents. We also include state fixed effects and year fixed effects. Standard errors are clustered at the city level. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel B: Validation: adaptation and insurance.

	Dependent variable:			
	Adapt	Hard Adapt	Soft Adapt	Adapt
	(1)	(2)	(3)	(4)
CRS Class Code	-0.06^{**}	-0.06^{**}	-0.03	-0.06^{*}
	(-2.37)	(-2.16)	(-1.31)	(-1.91)
Log(Population)	-0.03	-0.04	0.01	0.06
	(-0.49)	(-0.78)	(0.26)	(1.19)
Log(N Sentences)	0.78^{***}	0.74^{***}	0.16^{***}	0.59^{***}
	(11.57)	(11.20)	(3.47)	(10.30)
Measure	Main	Main	Main	Main+Bonds
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered s.e.	City	City	City	City
Observations	2,273	2,273	875	1,371
Adjusted R^2	0.57	0.57	0.10	0.58

Table B1: Validation of textual measures, continued.
Panel C reports validation via the market tests. In this table, *adaptation* is number of adaptation sentences in budgets, CAFRs, and bond prospectuses, scaled by the total number of sentences, winsorized at 1%, and standardized. *Hard* (*soft*) *adaptation* is number of hard (soft) adaptation sentences in budgets, CAFRs, and bond prospectuses, scaled by the total number of sentences, winsorized at 1%, and standardized. *Flood Risk* is the standardized percentage of properties at risk in a city. Columns (1)—(5) show a replication of the Painter (2020) regression of equation (1). The dependent variable is the offering spread, defined as the difference between offering yield and the maturity-matched yield from the MMA curve. We include control variables used in Painter (2020).t-statistics are reported in parentheses, with standard errors clustered by county. Columns (6)—(10) present replication of the Goldsmith-Pinkham et al. (2021) regressions of equation (1) on our data. The dependent variable is the volume-weighted average credit secondary spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the MMA curve. We include control variables used in Goldsmith-Pinkham et al. (2021). t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel C: Market Tests

	Dependent variable:									
	Offering Spread					Secondary Spread				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Flood Risk	1.51**	2.90***				4.25*	7.71**			
	(2.07)	(3.14)				(1.73)	(2.02)			
Adaptation × Flood Risk		−0.75*	−2.82***				−1.27	−1.88***		
		(−1.75)	(−5.11)				(−1.61)	(−3.80)		
Adaptation		−1.19*	1.95*				−2.61	−0.60		
		(−1.82)	(1.80)				(−1.26)	(−0.17)		
Hard Adaptation × Flood Risk				−2.59***					−1.76***	
				(−4.88)					(−3.62)	
Hard Adaptation				1.53					1.21	
				(1.46)					(0.33)	
Soft Adaptation × Flood Risk					−0.50**					−1.21***
					(−2.19)					(−2.96)
Soft Adaptation					0.03					1.05
					(0.05)					(0.61)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
County-Year-Month FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
State-Year FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Clustered s.e.	County + YM	County + YM	County + YM	County + YM	County + YM	County	County	County	County	County
Observations	42,861	42,861	42,861	42,861	42,861	235,746	235,746	235,746	235,746	235,746
Adjusted R^2	0.64	0.64	0.71	0.71	0.71	0.11	0.11	0.12	0.12	0.12

Table B2: Robustness: Validation of textual measures.
This table presents robustness to our validation regressions. Panel A presents the association between our measures and *Log*(*Fund Expense per Capita*), natural logarithm of total expenses from the city funds that are related to capital projects and emergency preparedness, scaled by city population. The dependent variables are *adaptation* that excludes drainage-related sentences (column (1)), *adaptation* that excludes stormwater-related sentences (column (2)), and *adaptation* that excludes both drainage- and adaptation-related sentences (column (3)). We control for the *Log*(*Population*), the natural logarithm of city-level population and *Log*(*N Sentences*), natural logarithm of the total number of sentences in city-level documents. We also include city and year fixed effects. Standard errors are clustered at the city level. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively. The number of observations in Panel A drops because Muni Atlas only has fund-level data for 2017-2020.

Panel A: Validation: adaptation and fund expenses.

	Dependent variable:		
	Adapt-Drain	Adapt-Stormwater	Adapt-Drain-Stormwater
	(1)	(2)	(3)
Log(Fund Expense per Capita)	0.05^{*}	0.06^{**}	0.03
	(1.69)	(2.13)	(1.10)
Log(Population)	0.64	1.39^{*}	2.32^{**}
	(0.57)	(1.90)	(2.45)
Log(N Sentences)	0.46^{***}	0.59^{***}	0.39^{***}
	(3.17)	(4.17)	(2.67)
Measure	Main	Main	Main
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Clustered s.e.	City	City	City
Observations	753	753	753
Adjusted R^2	0.91	0.91	0.85

Table B2: Robustness: Validation of textual measures, continued.
Panel B presents the association between our adaptation measures and the Community Rating System (CRS) class code. *CRS Class Code* indicates whether cities are eligible for the higher flood insurance discount from CRS (Community Rating System), an incentive program that allows cities with higher flood preparedness can receive a higher flood insurance discount. *CRS Class Code* decreases in preparedness, with a class code of 1 representing the highest level of preparedness with an insurance discount of 45%, whereas a class code of 10 represents the lowest level of preparedness with no insurance discount. The dependent variables are *adaptation* that excludes drainage-related sentences (column (1)), *adaptation* that excludes stormwater-related sentences (column (2)), and *adaptation* that excludes both drainage- and adaptation-related sentences (column (3)). We control for the $Log(Population)$, the natural logarithm of city-level population and $Log(N\ Sentences)$, natural logarithm of the total number of sentences in city-level documents. We also include state fixed effects and year fixed effects. Standard errors are clustered at the city level. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel B: Robustness Validation: adaptation and insurance.

	Dependent variable:		
	Adapt-Drain	Adapt-Stormwater	Adapt-Drain-Stormwater
	(1)	(2)	(3)
CRS Class Code	-0.07^{**}	-0.07^{**}	-0.06^{*}
	(-1.96)	(-2.12)	(-1.85)
Log(Population)	0.12^{*}	-0.04	0.11
	(1.74)	(-0.60)	(1.44)
Log(N Sentences)	0.68^{***}	0.77^{***}	0.63^{***}
	(8.38)	(9.70)	(8.08)
Measure	Main	Main	Main
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Clustered s.e.	City	City	City
Observations	2,273	2,273	2,273
Adjusted R^2	0.47	0.45	0.34

Table B2: Robustness: Validation of textual measures, continued.
Panel C reports validation via the market tests. In this table, *Adapt - Drain* is number of adaptation sentences hat exclude drainage-related sentences, scaled by the total number of sentences, winsorized at 1%, and standardized. *Adapt - Storm* is number of adaptation sentences hat exclude stormwater-related sentences, scaled by the total number of sentences, winsorized at 1%, and standardized. *Adapt - Drain - Storm* is number of adaptation sentences hat exclude both drainage- and stormwater-related sentences, scaled by the total number of sentences, winsorized at 1%, and standardized. All measures are based on budgets, CAFRs, and bond prospectuses. *Flood Risk* is the standardized percentage of properties at risk in a city. Columns (1)—(3) show a replication of the Painter (2020) regression of equation (1). The dependent variable is the offering spread, defined as the difference between offering yield and the maturity-matched yield from the MMA curve. We include control variables used in Painter (2020). t-statistics are reported in parentheses, with standard errors clustered by county. Columns (4)—(6) present replication of the Goldsmith-Pinkham et al. (2021) regressions of equation (1) on our data. The dependent variable is the volume-weighted average credit secondary spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the MMA curve. We include control variables used in Goldsmith-Pinkham et al. (2021). t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel C: Robustness: Market Tests

	Dependent variable:					
	Offering Spread			Secondary Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Adapt - Drain × Flood Risk	-2.06			-4.15^{***}		
	(-1.63)			(-4.33)		
Adapt - Storm × Flood Risk		-1.95^{***}			-2.04^{***}	
		(-3.73)			(-4.29)	
Adapt - Drain - Storm × Flood Risk			-2.60^{**}			-3.65^{***}
			(-2.15)			(-4.75)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year-Month FE	No	No	No	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	No	No	No
Clustered s.e.	County	County	County	County + YM	County + YM	County + YM
Observations	42,861	42,861	42,861	235,746	235,746	235,746
Adjusted R^2	0.71	0.71	0.71	0.12	0.12	0.12

Table B3: Placebo: Validation of textual measures.

This table presents robustness to validation regressions using placebo measure that captures police- and other safety-related sentences instead of our adaptation measures. Panel A replicates Table B1 Panel A with placebo measures. We control for the *Log*(*Population*), the natural logarithm of city-level population and *Log*(*N Sentences*), natural logarithm of the total number of sentences in city-level documents. We also include city and year fixed effects. Standard errors are clustered at the city level. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively. The number of observations in Panel A drops because Muni Atlas only has fund-level data for 2017-2020.

Panel A: Validation: adaptation and fund expenses.

	Dependent variable:	
	Safety/Police	
	(1)	(2)
Log(Fund Expense per Capita)	0.01	0.004
	(1.23)	(0.23)
Log(Population)	-0.15	-0.08
	(-0.58)	(-0.22)
Log(N Sentences)	0.60^{***}	0.54^{***}
	(7.59)	(8.28)
Measure	Main	Main+Bonds
City FE	Yes	Yes
Year FE	Yes	Yes
Clustered s.e.	City	City
Observations	753	483
Adjusted R^2	0.94	0.90

Table B3: Placebo: Validation of textual measures, continued.
Panel B replicates Table B1 Panel B with placebo measures. *CRS Class Code* indicates whether cities are eligible for the higher flood insurance discount from CRS (Community Rating System), an incentive program that allows cities with higher flood preparedness can receive a higher flood insurance discount. *CRS Class Code* decreases in preparedness, with a class code of 1 representing the highest level of preparedness with an insurance discount of 45%, whereas a class code of 10 represents the lowest level of preparedness with no insurance discount. We control for the *Log*(*Population*), the natural logarithm of city-level population and *Log*(*N Sentences*), natural logarithm of the total number of sentences in city-level documents. We also include state fixed effects and year fixed effects. Standard errors are clustered at the city level. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel B: Validation: placebo measures and insurance.

	Dependent variable:	
	Safety/Police	
	(1)	(2)
CRS Class Code	0.02	−0.01
	(0.79)	(−0.15)
Log(Population)	0.33***	0.38***
	(4.65)	(4.99)
Log(N Sentences)	0.83***	0.60***
	(5.91)	(3.17)
Measure	Main	Main+Bonds
State FE	Yes	Yes
Year FE	Yes	Yes
Clustered s.e.	City	City
Observations	2,273	1,371
Adjusted R^2	0.52	0.52

Table B3: Placebo: Validation of textual measures, continued.
Panel C replicates Table B1 Panel C with placebo measures. Column (1) show a replication of the Painter (2020) regression of equation (1). The dependent variable is the offering spread, defined as the difference between offering yield and the maturity-matched yield from the MMA curve. We include control variables used in Painter (2020). t-statistics are reported in parentheses, with standard errors clustered by county. Column (2) present replication of the Goldsmith-Pinkham et al. (2021) regressions of equation (1) on our data. The dependent variable is the volume-weighted average credit secondary spread of a municipal bond, defined as the difference between yield-to-maturity and the maturity-matched yield from the MMA curve. We include control variables used in Goldsmith-Pinkham et al. (2021). t-statistics are reported in parentheses, with standard errors clustered by county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel C: Placebo: Market Tests

	Dependent variable:	
	Offering Spread	Secondary Spread
	(1)	(2)
Safety × Flood Risk	−0.01	−0.01
	(−0.48)	(−0.27)
Controls	Yes	Yes
City FE	Yes	Yes
County-Year-Month FE	No	Yes
State-Year FE	Yes	No
Clustered s.e.	County	County + YM
Observations	42,861	235,746
Adjusted R^2	0.71	0.12

Appendix C: Robustness and sensitivity of textual measures.

To ensure the robustness of our results, we conduct sensitivity analyses for the assumptions we made when creating the textual measures. Our first set of sensitivity analyses compares the use of sentences versus words as our unit of analysis. We use sentences in our main analysis because each sentence likely reflects one activity, whereas one sentence can have multiple keywords that represent the same activity. Figure C1 plots the total number of adaptation keywords in the document over time and by flood risk. The overall trends are similar to that if we plot adaptation sentences for the same sample. Our second sensitivity analysis uses groups of texts instead of sentences as our unit of analysis. We define a group as two or more distinct adaptation keywords within five sentences. Figure C2 shows the number of groups over time and the trend is comparable to our main analysis using the number of sentences. In Figure C3, we further show that our assumption is not sensitive to the choice of group size or distance. The measure remains similar when we change the distance from five sentences to zero, 10, or 15, and when we increase the minimum number of keywords.

Figure C1: Number of keywords.
This figure shows the measures using the count of adaptation keywords in the dictionary instead of the number of sentences.

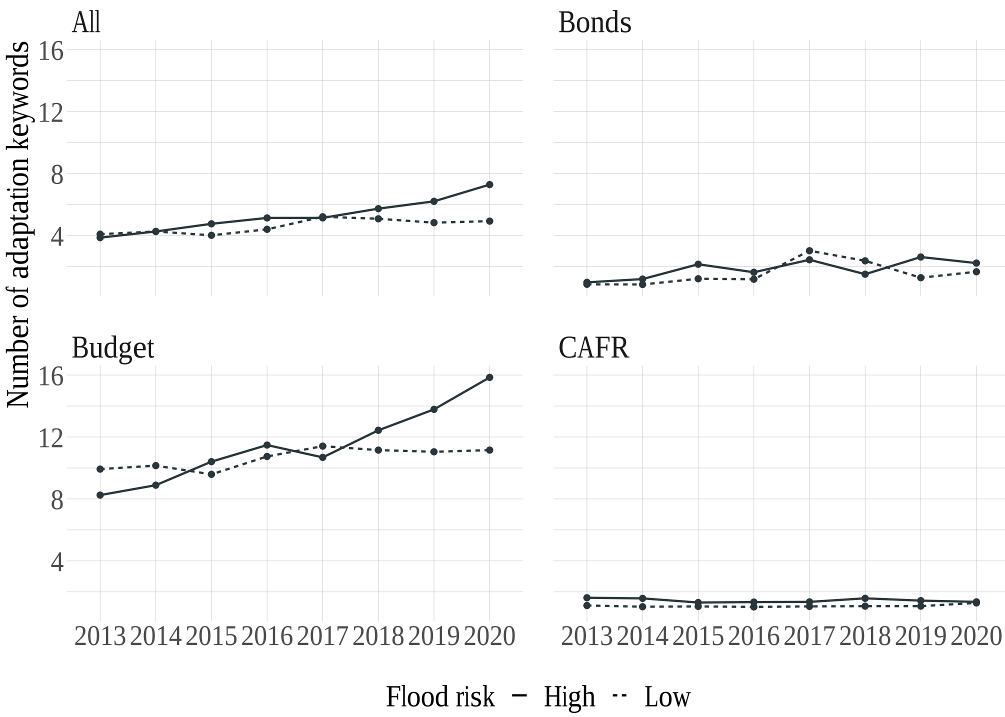


Figure C2: Number of groups.
This figure plots the number of groups containing adaptation keywords in a document. We define a group as two or more distinct adaptation keywords within five sentences.

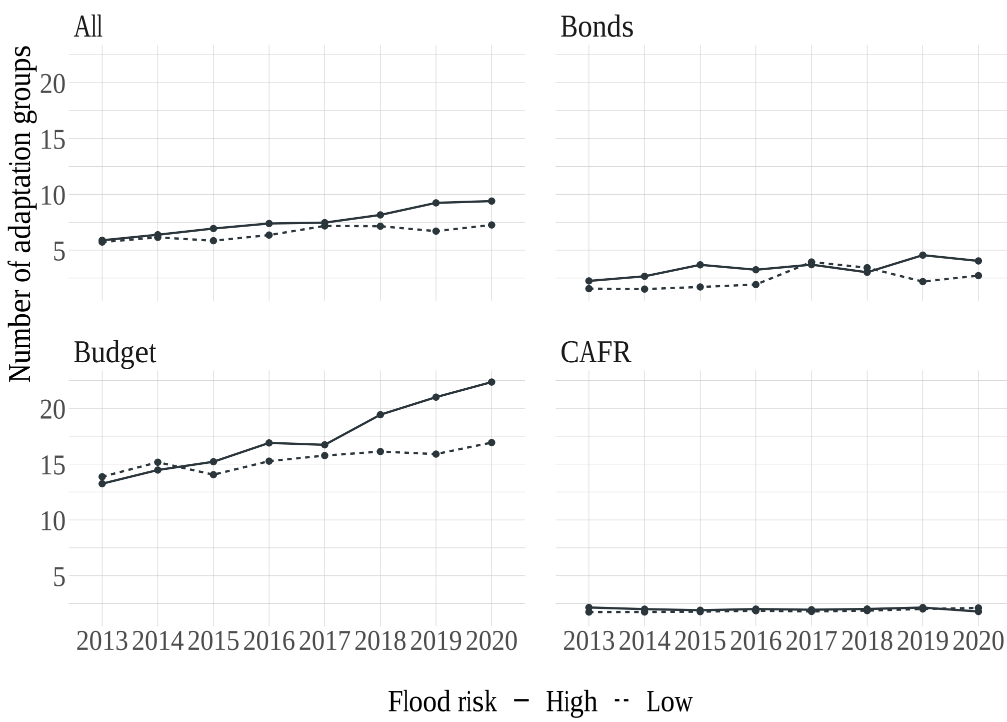
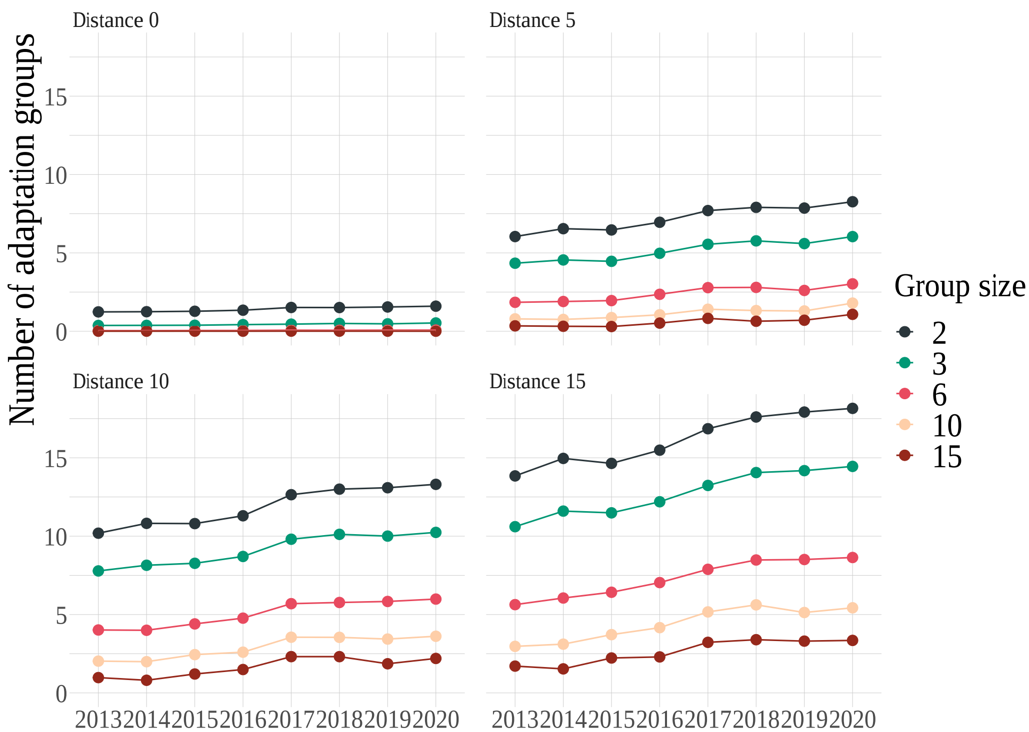


Figure C3: Sensitivity: Number of groups.
This sensitivity analysis evaluates the appropriate group size, where a group is defined as a certain number of keywords (size) within a certain number of sentences (distance). Size is the minimum number of keywords within a group. The four panels represent sensitivity by distance, which is the number of connected sentences that must include the keywords to be considered a group.



Appendix D: LDA topic analysis.

We use LDA to extract most common topics of the adaptation sentences. To improve the accuracy of the topics identified, we remove sentences that are likely tables from our textual data. Additionally, we eliminate common words that can obscure the topic classification such as ''fund" and ''city". We then review the topics obtained using the LDA model and choose to present the results using five topics, as a higher number of topics result in fewer distinct topics. We then manually read through the sentences that were identified by these five topics and labelled them as *Capital improvement projects, Program/department details, Funding allocation*, *Intended use of funds*, and *Personnel*. Below, we define the topics, and **Table D1** provides sample sentences for each of the topics.

The first topic, *Capital improvement projects*, captures sentences that describe details on the proposed capital improvement projects, such as repairing or installing catch basins. The second topic, *Program/department details*, provides details on the role of departments or programs related to adaptation, such as inspecting and managing stormwater capital improvement projects. These two topics are both most commonly found in budgets, where cities disclose information about capital improvement projects and describe the role of related departments and programs.

The third topic is *Funding allocation*, and covers descriptions of the funds spent or funding allocation for the capital projects, and it is more common in CAFRs. The fourth topic is labeled *Intended use of funds*, which captures the remaining tables that were not removed using our table identification approach.[6] These sentences pertain to adaptation-related projects or districts and specify the intended use of funds. This category is most often found in bonds. The fifth topic is *Personnel*, which captures generic sentences that list the names of personnel, and is equally common across all three types of documents.

[6]Because our textual data is obtained from PDF files, it is difficult to identify the tables, as they are not marked in any way. For the LDA analysis, LDA analysis we used a combination of sentence length and the ratio of numbers to letters to identify tables. This approach is not perfect. Consequently, LDA groups all table-like sentences into a separate topic.

Table D1: Topics and sentence examples.
This table interprets five topics we've classified our sentences into and provides examples of the sentences that fall into five topics.

Topic	Source	Sample sentence
Intended use of funds (Tables that include adaptation-related departments or districts or projects. Frequent topic in bonds when discussing the use of funds.)	Portland, OR 2019 Bond	BONDS PAID AND/OR SECURED BY THE GENERAL FUND A. Non-Self-Supporting Limited Tax Revenue Bonds $154,305,000 Limited Tax Pension Obligation Revenue Bonds (General Fund share) 59,242,982 Limited Tax Housing Revenue Bonds 12,370,000 General Fund-Secured Lines of Credit 43,268,965 Total Bonds Secured and Paid from the General Fund (1) $269,191,947 B. Self-Supporting Limited Tax Pension Obligation Revenue Bonds (Non-General Fund share) $100,335,364 Limited Tax Revenue Bonds (Streetcar) 9,125,000 Limited Tax Revenue Bonds (Convention Center – Visitor Development Initiative) 70,305,382 Limited Tax Revenue Bonds (Stadium Project – Visitor Development Initiative) 13,153,000 Limited Tax Revenue Bonds (JELD-WEN Field Project) 12,000,000 Limited Tax Revenue Bonds (Portland-Milwaukie Light Rail Project) 28,410,000 Limited Tax Revenue Bonds (Sellwood Bridge I & II) 67,505,000 Limited Tax Improvement Bonds 37,825,000 State Infrastructure Finance Authority Loan (Columbia River Levee Project) 702,785 FPDR Tax Anticipation Notes 35,725,000 General Fund-Secured Lines of Credit 42,257,454 Total Self-Supporting Bonds Secured by the General Fund $417,343,984 III.
	Mesquite, TX 2016 Bond	Proceeds from the sale of the Bonds will be used to (i) refund a portion of the City's Combination Tax and Revenue Certificates of Obligation, Series 2007, Combination Tax and Revenue Certificates of Obligation Series 2008 and General Obligation Refunding Bonds, Series 2008 as described on Schedule I attached hereto (the "Refunded Obligations") to lower the City's outstanding debt payments; (ii) constructing, improving, extending, expanding, upgrading and developing two-lane residential streets, including, utility relocation, landscaping, sidewalks, traffic safety and operational improvements, drainage, the purchase of any necessary right-of-way, and other related costs; and (iii) pay legal, fiscal, and other professional fees in connection with the issuance of the Bonds.
Capital improvement projects (Provide details on the proposed capital improvement projects. Describes new undertakings as well as improvements to the existing infrastructure.)	Miami, FL 2015 Bond	The improvements consist of one or a combination of the following: 1) Repair, replace, and/or install curbs and gutters, 2) Reconstruct and/or raise streets and sidewalks, 3) Repair, replace, and/or install collection systems, catch basins and manholes, 4) Construct water quality treatment devices, 5) Construct pump stations, controls and force mains, 6) Convert existing pumping stations discharge piping from injection wells and add force mains to new outfall, and 7) Repair or upgrade existing outfall pipes and seawalls (inclusive of tidal backflow prevention devices).
	Peoria, AZ 2018 Budget	The specific improvements will include clearing and grubbing, saw cut along existing pavement, install new pavement, micro-seal, curb, gutter, valley gutter and apron, sidewalk and ADA ramps, widening and installing drainage facilities, widening of the bridge and accommodating the Agua Fria River trail connection under the bridge, striping and signage, street lighting, and landscape and irrigation.
Funding allocation (Describes the funds spent/funding allocation for the capital projects.)	Pensacola, FL 2018 CAFR	DETAIL NOTES ON ALL FUNDS (Continued) General Fund Community Redevelopment Agency Urban Core Redevelopment Trust Eastside Tax Increment Financing District Fund Balance Non-spendable Inventories Prepaids 23,422 107 Subtotal non-spendable fund balance 23,422 107 - - Restricted Wastewater treatment plant relocation Redevelopment Rev Bond(s) debt payments Stormwater projects Section 8 program administrative Natural disaster projects General government 282,690 Transportation 95,818 Physical Environment Saenger capital 334,378 DOJ Equitable Sharing Agreement Public safety 137,358 Community development projects 4,679,835 654,563 Culture and recreation 188,268 Building inspections Local Option Sales Tax debt payment SHIP Program HOME Program Subtotal restricted fund balance 1,038,512 4,679,835 - 654,563 Committed Council Reserve 13,522,262 Tree landscape 391,414 Park purchases 103,559 Stormwater projects Subtotal committed fund balance 14,017,235 - - - Assigned General government 2,677,660 Demolition 367,803 Lien amnesty 25,407 Housing Initiatives Fund 146,519 Inner City Housing Initiatives 440,490 Economic Development 933,580 Culture and recreation Other assigned Subtotal assigned fund balance 4,591,459 - - - Unassigned 208,800 Total Fund Balance 19,879,4284, 679, 942 -654, 563 Major Funds CITY OF PENSACOLA, FLORIDA NOTES TO FINANCIAL STATEMENTS SEPTEMBER 30, 2018 119 NOTE III.
	Tampa, FL 2018 Budget	AREAS UNDER CONSIDERATION: Not Applicable Actual to Date Budget to Date Budget FY18 Budget FY19 Budget FY20 Budget FY21 Budget FY22 Budget All Years COST ESTIMATES: $1,086,177 $1,125,450 - - - - - $1,125,450 20-Land - - - - - - - - 30-Construction/Improvements 1,075,454 1,114,650 - - - - - 1,114,650 31-Design/Professional Services - - - - - - - - 40-Engineering/Inspection - - - - - - - - 50-Project Management - - - - - - - 51-In House Labor 10,723 10,800 - - - - - 10,800 60-Aids to Other Governments - - - - - - - - 70-Equipment - - - - - - - - 80-Computer Hardware/Software - - - - - - - - 90-Public Art - - - - - - - - FUNDING SOURCES: - - - - - - 167 CAPITAL IMPROVEMENT PROJECT (FY18 - FY22) PROJECT TITLE: Knights Avenue: Lynwood Avenue to MacDill Avenue Flooding Relief PROJECT ORGANIZATION: TSS-Transportation Stormwater Dept PROJECT NUMBER: PR_1001021 CITY COUNCIL DISTRICT: District 4 PROJECT LOCATION: 3303 West Knights Avenue PROGRAM: Stormwater PROJECT DESCRIPTION: DISTRICT MAP ID NUMBER: ST29 This project provides for localized flooding relief along Knights Avenue: Lynwood Avenue to MacDill Avenue.
Program/department details (Provides details on adaptation-related programs/activity/department's roles. Often involves verbs such as "provide" and "maintain".)	Austin, TX 2014 Budget	This is accomplished by 1) creating and maintaining floodplain engineering models and maps; 2) coordinating the City's participation in the National Flood Insurance Program and Community Rating System; 3) providing floodplain information to the public; 4) reviewing floodplain development applications and processing floodplain variance requests; and 5) providing opportunities for private/public partnership funding for regional drainage improvements, as an alternative to private development providing on-site detention to mitigate flood hazard increase.

	Kenosha, WI 2018 Budget	7-3 STORMWATER UTILITY (SWU) Engineering, Inspection and Enforcement The Engineering, Inspection and Enforcement division of the Stormwater Utility manages the Stormwater Utility database of parcel information for approximately 32,400 customers; reviews, permits and inspects construction site's erosion control; responds to complaints regarding construction erosion control; responds to drainage complaints in the right-of-way and private property; is responsible for designing, bidding, inspecting and managing stormwater capital improvement projects; is responsible for designing and coordinating utility projects that utilize Stormwater Utility personnel; manages the Stormwater Utility credit and adjustment application submittals; manages the inspection of city-owned stormwater management facilities; implements and enforces the requirements of the long term maintenance procedures; and implements and manages a stormwater quality management program for compliance with permit requirements.
Personnel (A list of personnel, including the people involved in adaptation.)	Bryan, TX 2019 CAFR	P. Mans Executive Director/CEO ee soggenpeesomra _x000C_ PRINCIPAL OFFICIALS GOVERNING BODY: Andrew Nelson Mayor Greg Owens Mayor Pro Tem Reuben Marin City Council Prentiss Madison City Council Mike Southerland City Council Brent Hairston City Council Sheldon "Buppy" Simank City Council OTHER PRINCIPAL OFFICIALS: Kean Register City Manager Hugh Walker Deputy City Manager – Support Services Joseph Dunn Deputy City Manager – Community Services Janis Hampton City Attorney Mary Lynne Stratta City Secretary Joe Hegwood Chief Financial Officer Gary Miller General Manager – Electric Utilities Services Jayson Barfknecht Public Works Director Eric Buske Police Chief Randy McGregor Fire Chief xv 'Municipal Court 'Administration Chad Eixmann Neighborhood/ Youth Services Bubba Bean Communications « Marketing Kala McCain Legislative Services Citizens City Council City Secretary Mary Lynne Stratta Municipal Court Judge Albert Navarro City Manager Kean Register City Internal Auditor Robert Shultz City Attorney Janis Hampton Chief Financial Joe Hegwood Public Works Fire & EMS Officer Jayson Barfknecht Randy McGregor COBAssistant Engineering Finance Director Paul Kaspar 'Will Smith Purchasing Traffic Operations Karen Sonley Fleet Services BTU Fiscal Services Bobby Walker Kristi Nash Solid Waste, BTU Risk Streets Drainage Planning EricZaragoza Doug Lyles Animal Services Julianne Burkhalter Water Water Production & Field Operations Charles Rhodes Wastewater Treatment & Compliance Mark Jurica Warehouse Enviornmental Compliance / Code — Enforcement Administrative Services Hugh Walker Community Services Joey Dunn Human Resources Kari French Library Services Larry Koeninger Risk Management Strategic Projects Cindy Kirk.

Appendix E: Data collection and processing.

Disclosure data.

We hand-collected budgets, CAFRs, and bonds for our sample cities. We sourced budgets and CAFRs by searching individual city websites. When searching for the budgets, we noticed that sometimes cities produce a list of budget tables in addition to the annual budgets. We excluded these tables from our analyses, and instead collected full annual budget documents that have text describing the budget, Mayor message, description of risks, etc. Unfortunately, cities' websites often only provide the directory of Annual budget/Annual financial report documents for a few recent years (typically three to five years). If needed documents were unavailable on the city website, we searched Electronic Municipal Market Access (EMMA) and Wayback Machine snapshots of the city website to identify the missing documents. If we couldn't identify the disclosures using these sources, we contacted city officials via email and requested copies of the missing documents. We downloaded the bond prospectuses from the EMMA website.

To ensure that our documents correspond to the same time period, we align timing based on the document publication date. Specifically, we define year as the fiscal year for the CAFRs, the fiscal year minus one for annual budgets (budgets are forward-looking and we want to capture cities' plans when they were prepared), and as calendar year for bonds prospectuses. To illustrate, consider Tampa, FL. Its 2017 fiscal year ended on September 30, 2017. The CAFR for that fiscal year was released in March 2018. The closest publication of a budget is in September 2017 for fiscal year 2018. Bonds prospectus were published throughout the year. As such, for our defined year 2017, we include CAFR for fiscal 2017, budget for fiscal 2018, and bonds that are issued in the calendar year 2017.

While there is only one CAFR and one budget per city-year, there can be multiple city-year observations for bonds. For our analysis, we first aggregate our textual measures to a city-year, report-type level. For bonds, we take the average textual measure across documents since there are sometimes multiple bonds issued in a given year. For budgets, we aggregate the textual measures for years where there are multiple parts to a budget. We use this strategy instead of taking the average for the different parts because the budgets contain similar components every year and are more comparable when aggregated.

Disclosure cleaning procedure.

Our collected documents were in PDF format. Some documents, especially those in earlier years, are scanned (either fully or a portion of documents). We use Optical Character Recognition (OCR) software Python-tesseract and ABBYY FineReader to convert the images into machine-readable text. Next, we convert them to text via Python using several packages. We use the package Apache Tika to extract texts from the disclosure documents. We then tokenize the texts into sentences using NLTK tokenizer. Next, we clean the text by removing stopwords using NLTK, by converting all letters to lowercase, by removing special characters and numbers, and by replacing multiple whitespaces by single space. Finally, we stem all words using the NLTK Snowball stemmer, so that words like ''flooding" and ''floods" convert to ''flood."

Appendix F: Capital budget outlook example.

Figure F1: Tampa budget 2018.
This figure presents an extract from Tampa's 2018 budget, where the city allocates $9 million over five years to a stormwater improvement project for flooding relief.

CAPITAL IMPROVEMENT PROJECT (FY18 - FY22)

PROJECT TITLE:	Stormwater Improvements Annual Contract FY2018 – FY2022	**PROJECT ORGANIZATION:**	TSS-Transportation Stormwater Dept
PROJECT NUMBER:	PR_1001177	**CITY COUNCIL DISTRICT:**	Citywide
PROJECT LOCATION:	Citywide	**PROGRAM:**	Stormwater
PROJECT DESCRIPTION:		**DISTRICT MAP ID NUMBER:**	N/A

This project provides for small to medium sized flooding relief and failed pipe projects will be constructed under this city wide contract.

AREAS UNDER CONSIDERATION:
Not Applicable

	Actual to Date	Budget to Date	Budget FY18	Budget FY19	Budget FY20	Budget FY21	Budget FY22	Budget All Years
COST ESTIMATES:	-	-	**$3,000,000**	-	-	**$3,000,000**	**$3,000,000**	**$9,000,000**
20-Land	-	-	-	-	-	-	-	-
30-Construction/Improvements	-	-	3,000,000	-	-	3,000,000	3,000,000	9,000,000
31-Design/Professional Services	-	-	-	-	-	-	-	-
40-Engineering/Inspection	-	-	-	-	-	-	-	-
50-Project Management	-	-	-	-	-	-	-	-
51-In House Labor	-	-	-	-	-	-	-	-
60-Aids to Other Governments	-	-	-	-	-	-	-	-
70-Equipment	-	-	-	-	-	-	-	-
80-Computer Hardware/Software	-	-	-	-	-	-	-	-
90-Public Art	-	-	-	-	-	-	-	-
FUNDING SOURCES:			**$3,000,000**	-	-	**$3,000,000**	**$3,000,000**	**$9,000,000**
Assessment Revenues			-	-	-	3,000,000	-	3,000,000
Debt Proceeds			3,000,000	-	-	-	3,000,000	6,000,000

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Appendix G: Determinants of the adaptation gap–alternative definitions.

Table G1: Robustness: Determinants of the Adaptation Gap.
This table reproduces Table 5 Panel A with the alternative definitions of *Adapt Gap*. Column (1) defines *Adapt Gap* as an indicator that equals to one if the residuals from the Table 4 Panel A regressions are negative. Column (2) defines *Adapt Gap* as an indicator that equals to one if the residuals from the Table 4 Panel A regressions are less than –0.5. Column (3) defines *Adapt Gap* as an indicator that equals to one if the residuals from the Table 4 Panel A regressions are less than –1. *Republican* is an indicator variable equal to one if the city has a Republican mayor. *UFB/Total Expense* is unrestricted fund balance scaled by total expenses. *Total Debt per Capita* is total debt outstanding scaled by the population of the city. *Capital Budget Outlook* is the reported number of years in the capital budget. We also include state and year fixed effects. Standard errors are clustered at the state level. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

	Dependent variable:		
	I(Res < 0)	I(Res < -0.5) Adapt Gap	I(Res < -1)
	(1)	(2)	(3)
Republican	0.04	0.04	0.03
	(0.96)	(1.16)	(1.02)
UFB/Total Expense	-0.06^{**}	-0.06^{***}	-0.03^{**}
	(-2.34)	(-3.09)	(-2.42)
Log(Total Debt per Capita)	-0.03	-0.04^{**}	-0.02
	(-1.49)	(-2.04)	(-1.28)
Capital Budget Outlook	-0.04^{***}	-0.02^{**}	-0.01^{*}
	(-3.25)	(-2.43)	(-1.92)
Measure	Main	Main	Main
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Clustered s.e.	State	State	State
Observations	2,614	2,614	2,614
Adjusted R^2	0.04	0.05	0.03