Measuring Cities' Climate Risk Exposure and Preparedness

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Abstract

We construct new time-varying linguistic measures of city-level climate exposure and adaptation from cities' budgets, annual reports, and bond prospectuses. We focus on flood risk, which enables us to construct a precise dictionary of climate exposure and adaptation keywords. We validate our measures by (1) showing increases in our textual measures after major climate events, and (2) showing that adaptation measures are associated with charges to capital and emergency funds. We also use our measure to test the importance of political, financial, and planning factors for climate-change adaptation. Preliminary results from a pilot study of 60 cities in Florida show that adaptation is lower in cities that have Republican mayors, and that our textual measures explain the pricing of municipal bonds.

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1 Introduction

Climate change is an increasing risk for cities, but we currently have limited information on how cities are preparing (if at all) for the adverse effects. Extreme weather events, from Hurricane Sandy that left New York City powerless, to Hurricane Irma that caused over US$50 billion in damage to Florida cities, have highlighted cities' vulnerability. The frequency of extreme weather events accelerated over the years, and summer 2021 brought more news about devastating disasters hitting cities across the globe.[1] Climate risk exposure creates a demand for information from various parties. For example, the investment community examines city-level preparedness when making investment decisions (BlackRock, 2019) and assigning credit ratings (Moody's, 2017a; S&P, 2017; Fitch, 2017). Concurrent research exploring the pricing of climate risks also needs reliable data to capture climate risks (Painter, 2020; Goldsmith-Pinkham et al., 2021).

The existing climate risk measures are limited, however, because they are based on geophysical data and lack information about city-level preparedness. Omitting city's adaptation actions and plans can lead to incorrect inferences about climate risks. For example, for two neighboring cities facing the same chance of flooding, the city with more adaptation infrastructure will incur less damage from an adverse climate event. Much of the information on existing infrastructure and future adaptation plans reside within cities, and is not in a standardized format.[2]

In this paper, we construct time-varying city-level climate exposure and preparedness measures using textual analysis of cities' financial disclosures. This approach has several advantages. While cities do not usually publish a standalone preparedness plan, they are required to regularly dis-

[1] See, for example, *Heavy Rains Pound New York City, Flooding Subway Stations and Roads*, New York Times, July 8, 2021; *Climate change blamed for devastating German floods*, Financial Times, July 16, 2021; *China flood death toll rises to 33, stoking its climate change concerns*, Financial Times, July 22, 2021; and *A 3°C world has no safe place*, The Economist, July 24, 2021.

[2] The most granular infrastructure assessment by an outside party is the "Report Card for America's Infrastructure" by the American Institute of Architects, which does not happen every year or for every state.

close such information as part of their financial disclosures. Thus, we take advantage of the unique richness of municipal financial disclosures. Cities' annual reports and bond prospectuses disclose material climate risks, which reflect the conditions of the current adaptation infrastructure. In budgets, cities provide forward-looking information about planned adaptation projects for addressing climate risks.

We make two choices when developing our textual analysis methodology. First, we capture the ratio of sentences containing keywords from a dictionary (Gentzkow et al., 2019). This method is similar to recent literature examining climate risks in the corporate setting; it also provides a simple and transparent interpretation of our textual measures (Li et al., 2020; Nagar and Schoenfeld, 2021). Second, we focus on flood risks. Increased flood risk is a consequence of climate change, as warmer planet temperatures contribute to heavier precipitation, an increased number of hurricanes, and the rise in sea level (Berardelli, 2019). Flood risks stem from a distinct set of weather events and can be addressed by investing in a specific set of infrastructure solutions (e.g., Ward et al., 2017; Jongman, 2018), which allow us to develop an accurate dictionary of keywords.

We develop two measures for a city's climate risks: climate exposure and climate adaptation. *Exposure* captures discussions about flood-related hazards, such as hurricanes and high tides. *Adaptation* measures the planned and existing infrastructure projects that local governments undertake to adapt to the threat of flood risks, such as the building of flood walls. For each measure, we create an initial dictionary by extracting keywords from the guides and reports from the Carbon Disclosure Project ("CDP"), the C40 Cities Climate Leadership Group, and the Intergovernmental Panel on Climate Change ("IPCC"). Next, we augment the dictionary with words and expressions that we manually identify by reading disclosures from a subsample of cities over time. This process allows us to capture common words that are used by cities, but not used in the guides and reports. Some examples include "king tide," "swale restoration," and "tidal valve." Our current

dictionaries for exposure and adaptation contain 42 and 113 keywords, respectively.

Comment for the reviewer: Below, we describe our analyses from a pilot study we run on 60 Florida cities. In a full study, we will replicate the following steps on a larger sample.

We conduct a pilot of our textual analysis methodology using 60 Florida cities. These cities are the 30 largest cities by population that are above and below the median city-level flood risk in Florida. In our full analysis, we plan to collect data and apply the same textual analysis methodology for 861 cities in 48 states and the District of Columbia. On average, in each financial report, a city discloses 11 sentences about climate exposure and 18 sentences about adaptation. We find the highest level of disclosure in budgets, followed by bond prospectus, and then annual reports.

After constructing our climate measures, we conduct a battery of validation and sensitivity tests to ensure that our measure picks up meaningful variation in a city's climate risk exposure and adaptation. To validate our exposure measure, we plot the time series of our textual measures and test whether *exposure* increases around major hurricanes. In the Florida sample, we observe an increase in *exposure* starting in 2016, which is the year that Hurricane Matthew hit Florida. In the full sample with multiple states, we can further exploit the staggered timing of hurricanes to verify our textual measures. To validate our adaptation measure in the Florida sample, we test if a higher level of *adaptation* translates into increased spending on infrastructure projects. We find suggestive evidence that *adaptation* is positively correlated with a city's expenses from capital improvement and emergency-related funds.

Having established that our measures capture climate exposure and adaptation, we explore what explains variation in cities' adaptation decisions. We study four economically significant city characteristics that are debated in the literature, and we expect to have meaningful interpretation of the results regardless of the future outcomes of our tests. First, we examine the association be-

tween political affiliation and adaptation. While political affiliation can shape beliefs as well as real economic decisions (e.g., Gerber and Huber, 2010; Dagostino et al., 2020; Kempf and Tsoutsoura, 2020), it is not apparent that affiliation will also affect adaptation decisions, especially for city officials in places that already face elevated flood risks. To capture any variation in beliefs that might not be picked up by political affiliation, we look at public opinion on whether local officials should address climate change more aggressively. We also examine the length of the capital budget outlook to identify whether cities with a more extended capital budget outlook can better plan for climate events, which are a long-term risk. Finally, we include credit constraints. Because adaptation is costly, credit constraints can explain why some cities are not investing in adaptation, even if there is a public demand and long-term budget planning.

Next, we use our measure to provide evidence on the extent to which adaptation is priced in municipal bond spreads. If investors demand a higher return for bonds with climate risk, we expect to see a positive correlation between bond spreads and climate risk. At the same time, if adaptation lowers the negative impact from the climate risk exposure, we expect to see a negative correlation between bond spreads and our textual measure of adaptation. We replicate two prior papers that study the pricing of climate risk in the municipal bonds market in order to estimate the incremental contribution of our measure: Painter (2020) in the primary issuance market and Goldsmith-Pinkham et al. (2021) in the secondary trading market.

Our study makes several contributions. First, our work is the first to complete a climate-change textual analysis of municipal disclosures and to document its properties. Similar work has measured climate risk for firms (e.g., Li et al., 2020; Engle et al., 2020), or has examined other textual features of municipality disclosures (e.g., Guo et al., 2009; Rich et al., 2016). However, it is important to understand cities' climate risk, as cities have concentrations of people and businesses that can be affected by related adverse events. City budgets are also publicly available, which is

a unique feature that enables us to measure the forward-looking actions planned by cities. We construct a city-specific climate dictionary and a novel dataset that can be used in future research to study cities' climate risk and preparedness levels. Furthermore, we will make the data readily available after our study, which can facilitate future research on city's climate risk.

Second, our paper provides evidence on the factors that explain why some cities are less prepared for climate risks. We examine how beliefs, the capital budget outlook, and credit constraints all correlate with our measure of adaptation. Understanding these factors should be of interest to policymakers, as it may help them tailor policy solutions. For example, if credit constraint is a key predictor of adaptation, future research can investigate the causal importance of credit constraints, and policymakers can consider credit lines as a potential solution.

Our measure captures city-level adaptation directly, which allows us to study the factors behind a city's lack of climate-change preparedness. In contrast, existing measures tend to proxy for city adaptation. For example, the Urban Adaptation Assessment by the Notre Dame Global Adaptation Initiative proxies for city-level "readiness" using a broad range of city-level socio-economic characteristics, e.g., debt per capita and the public opinion about the impact of climate change.[3] By measuring adaptation directly, we can empirically examine which city-specific characteristics are actually associated with adaptation.

Third, we contribute to the literature on how the market prices climate risk. Existing papers study the pricing of climate risk in equity securities, real estate prices, and insurance policies (e.g., Bernstein et al., 2019; Jerch et al., 2020; Giglio et al., 2021; Sen and Tenekedjieva, 2021). Prior municipal literature focuses on climate measures that capture the rise in sea level, and finds evidence that climate risks are priced in the market. Painter (2020) finds that the costs of bond issuance only increase with climate risks for long-term securities. He also finds that the results are strongest af-

[3] https://gain.nd.edu/assets/293226/uaa_technical_document.pdf

ter the Stern Review is published in 2006, which suggests that investor attention affects the pricing of climate risks. Goldsmith-Pinkham et al. (2021) finds that the market starts pricing exposure to the rise in sea level after 2011, and that this effect is concentrated on the East and Gulf coasts where the storm risk is highest. Both Painter (2020) and Goldsmith-Pinkham et al. (2021) use geophysical information to determine the climate risk from the rise in sea level. In contrast to these studies, the granularity of our data allows us to enhance the climate risk assessment of our sample cities. We extract city-specific components from financial disclosures that contain forward-looking information on city actions. These data will allow us to distinguish between cities that face similar geophysical risk, but that have different overall climate risk because they invest differently in adaptation.

2 Sample and Data

2.1 Municipal disclosures

We examine three types of disclosures: Comprehensive Annual Financial Reports ("CAFRs"), annual budgets, and the bond prospectuses issued by cities. The use of each of the financial disclosures has its advantages. Budgets are forward-looking disclosures and include discussions of important topics for a city's future and the allocation of funds for future projects. Comprehensive annual financial reports provide information about the city's past fiscal year. They include an overview of the city's material activities and discussions of the city's major risks. Bond prospectuses often describe the intended use of funds, and provide a high-level overview of the city and of risks that are relevant to bondholders.[4]

Additionally, we chose these sources because they are regularly produced, and are credible and comparable across cities and time. These documents are released by city governments, where of-

[4]General Obligation bonds are issued without a specific project in mind, but tend to describe projects that need funding.

ficials will face consequences for misrepresentation. CAFRs are audited, budgets are often subject to city legislative approval, and the people who create bond prospectuses are subject to civil liability for the misrepresentation or omission of material information. Finally, these documents are disclosed more regularly than other disclosures, such as those on websites and in educational pamphlets. CAFRs and budgets are annual disclosures, and bonds can be issued multiple times a year. This higher disclosure frequency allows us to compare the times series of disclosures.

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.

To ensure comparability across report types, we align timing using the approximate date of publication. Using the city of Tampa as an example, we see that the fiscal year for 2017 ended on September 30, 2017. The CAFR for fiscal year 2017 was released in March 2018. The closest publication of a budget is in September 2017 for fiscal year 2018. Bond prospectus happens throughout the year, and we use all bonds issued in calendar year 2017. In other words, we define the CAFR as of the report date for the given fiscal year, the annual budget as of the report date for the following fiscal year, and bonds as any bonds issued within the calendar year.

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 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.

2.2 Other data

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 geological 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 a high flood risk of 40%, while Orlando (inland) has a low flood risk of 6%. **Table 1** shows that on average, flood risk is 8.59%.

Financial and demographic data come from Muni Atlas, which has information on medium-sized local governments with sufficient financial data. For financial variables, we use data on city's outstanding debt and fund expenses. For demographic variables, we include annual population, which is based on the American Community Survey that is published once a year. From Muni Atlas, we also retrieve the six-digit CUSIP number associated with each city, which helps us identify bond prospectuses on EMMA.

2.3 Future sample collection

We plan to collect municipal financial documents from 2013-2019 for 861 cities in 48 states and the District of Columbia. This sample is comprised of cities with financial data from Muni Atlas as well as flood risk data from First Street Foundation, and which also have a 2010 census population

of over 40,000 people. We limit our sample to cities with a larger population because the annual budgets of smaller cities are sometimes displayed only as tables, as opposed to a full document with detailed information on budgeted items. Though the population of 40,000 is the current cutoff in our Florida pilot study, we may adjust this number if we observe different patterns in other states.

We focus on cities because they are the first line of local defense against climate hazards. In contrast to states and counties, cities are incorporated as clearly defined geographical areas, and have the ability to collect the most precise information about potential climate change consequences. Cities are also important economic centers with a concentrated population. Additionally, the Global Commission on Adaptation highlights the role that cities play in climate adaptation, since many cities are coastal. The Commission also finds that cities with good adaptation strategies pay a tenth of the normal costs from climate hazards Global Commission on Adaptation (2019).

The full sample will include around 18,081 (7 years $\times$ 3 document types $\times$ 861 cities) documents. **Table 1** shows the summary statistics of the population and of the flood risk measure for cities from each state in our sample. Louisiana, Florida, South Carolina, and Mississippi are some states with the highest flood risk. On average, cities in our sample have a population of 133,607, where 8.59% (or 5,283) of properties are at risk of flooding.

We are optimistic about our ability to come close to collecting the full sample of financial disclosures. For our Florida pilot study, we collected 411 budgets and 412 CAFRs from 60 cities over 7 years (out of a total of 420 documents for each document type). 9 budgets and 8 CAFRs are currently missing because the cities could not provide these documents to us yet. The number of budgets that we use in our analyses went down to 397 because 14 budgets were comprised of tables and did not contain sentences. We collected 295 bond prospectuses, which is a complete set based on Mergent Municipal data on bond issuances. Because some cities issue multiple bonds per year,

this amount translates into 154 city-year bond observations.

Throughout our analysis with the Florida pilot, we will provide power calculation based on the full sample size to estimate a minimum detectable effect size. We follow the power calculation based on Null Hypothesis Significance Testing (Cohen, 1992; List et al., 2011). For each analysis, we estimate δ, the minimum detectable effect size, based on the following equation from List et al. (2011), assuming similar size and variance of the treatment and control group:

$$\delta = (t_{\alpha/2} + t_{\beta})\sqrt{\frac{2\sigma^2}{n}} \tag{1}$$

where n is the sample size based on 18,081 documents for 861 cities. σ is the standard deviation of the outcome variable. We follow the standards in the literature and assume a significance level of 0.05 and a power of 0.80, which translates to $t_{\alpha/2}$ of 1.96 and t_{β} of 0.84 based on a standard normal table. Intuitively, based on the above equation, we are able to detect a smaller effect size if the sample size is higher, if the variance of the outcome variable is smaller, or if we relax the significance level or power.

3 Measuring Climate Risk Exposure and Adaptation

In this section, we explain how we apply textual analyses to create measures that quantify climate risk exposure and climate adaptation actions. We also validate that our measures capture meaningful variation in how local governments prepare for climate change.

3.1 Defining climate risk exposure and adaptation

Our goal is to create two distinct measures about climate risk using textual analyses of a city's financial disclosures. Specifically, we create two dictionaries to capture two separate measures.

The first measure is climate risk *exposure*, which is defined as the magnitude of impact that

climate change can have on a city. The *exposure* dictionary contains words on flood-related acute natural disasters and chronic weather events like hurricanes and the rise in sea level. While *exposure* is closely related to a city's geophysical flood risk, it may contain other, additional information. Specifically, cities may know more about the potential impact that a flood risk can have on their local community; the extent of impact can vary even for cities with similar geophysical conditions. We interpret a higher *exposure* as a larger impact of climate risk on a city.[5]

The second measure is climate *adaptation*, which is defined as the capital improvement projects undertaken to mitigate climate risk exposure. The *adaptation* dictionary contains words that are related to the infrastructure and projects used for flood adaptation, including "seawall" and "flood wall." Conceptually, climate adaptation reduces the negative impact from climate risks. These two dictionaries are mutually exclusive, i.e., if "flood wall" is included in the *adaptation* dictionary, we exclude "flood wall" from the *exposure* dictionary.

For both dictionaries, we start by creating an initial keywords list by examining the following documents: (i) the 2020 reporting guidance for cities in the Carbon Disclosure Project ("CDP"), (ii) the climate hazard taxonomy issued by the C40 Cities Climate Leadership Group, and (iii) the climate change summary for policymakers that is issued by the Intergovernmental Panel on Climate Change ("IPCC"). These documents contain the formal descriptions of climate change hazards and adaptation measures.

Next, we manually read the disclosures from a sample of cities over time to find additional, relevant words for the keywords list. In the Florida pilot analysis, we examine the reports of five cities: Fort Lauderdale, Miami, Miami Beach, Orlando, and Tampa. This allows us to capture words that local governments use to describe climate hazards or adaptation actions, but that may not be

[5]We acknowledge the concern that cities with a strong belief in climate change may disclose more information about climate risks. In Section 4, we explicitly study the effect of belief on our measures, and discuss the implications.

commonly used in guidance and reports issued by other organizations. Some examples include "king tide," "rainstorm," and "stormwater improvement project."

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., "hurricane)," while the bigrams capture keywords that would pick up irrelevant sections 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 of the bigrams. If only a few bigrams are irrelevant, we keep the unigram in the keyword list, but exclude the irrelevant bigrams. One example is the unigram "lightning." Most references to lightning are correctly referencing to the natural hazard, except for the bigram "Bay Lightning" (referring to the Tampa Bay Lightning ice hockey team), which we exclude. 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. One example is the unigram "stormwater," which can appear over a thousand times in a single document because of references to a stormwater utility, system, or fund. In such cases, we drop the unigram and keep relevant bigrams, such as "stormwater runoff."

Finally, using our updated list of keywords, we manually examine disclosures where there are more than 100 references to a given keyword. When the keywords pick up irrelevant phrases, we update the keywords list. In some cases, we keep an unstemmed keyword if the stemmed version is too general. For example, we keep the full word "subsidence," because the stemmed version "subsid" picks up irrelevant words like subsidy. We repeat this process multiple times to finalize our keywords dictionary. The current list of keywords can be found in **Table 2 Panel A**.

3.2 Textual analysis methodology

After collecting all the documents as PDFs, we convert them to text on Python using several packages. We use the package pdfplumber to extract texts from the disclosure documents. Some budgets, especially those in earlier years, are scanned, which means that the texts are not picked up by the pdfplumber package. For these samples, we use Optical Character Recognition Abby to convert the images into texts. We then clean the text by removing stopwords using NLTK, and by converting all letters to lower case. Next, we stem all words using the NLTK Snowball stemmer, so that words like "flooding" and "floods" convert to "flood." Finally, we tokenize the texts into sentences using NLTK tokenizer.

We apply the two keyword dictionaries to the cleaned texts from the local government disclosures, and create textual measures for exposure and adaptation. Our textual measure captures the number of sentences that contain keywords from the corresponding dictionary, scaled by the total number of sentences in a document, and multiplied by 10,000. This measure captures the ratio of climate-related sentences in a document. We use sentences instead of word counts to reduce noise and to prevent outliers that are driven by a few keywords. In Section 3.5, we discuss robustness tests where we repeat the main analysis using the count of keywords.

3.3 Descriptive statistics

Comment for the reviewer: In what follows, we describe the preliminary summary statistics for the pilot study on 60 Floridian cities. In a full study, we will replicate these steps on a larger sample.

To illustrate how our textual measure works, **Table 2 Panel B** provides examples of sentences that contain words from each of the two dictionaries. In **Table 2 Panel C**, we include paragraphs from Miami Beach's disclosures to illustrate how we convert these paragraphs into the scaled mea-

sures used in our analysis, and to help readers gauge the size of these measures. In the first paragraph, two of the five sentences contain adaptation keywords. As the entire document contains a total of 1725 sentences, these 2 sentences contribute to the total scaled adaptation measure by 11.59 (2/1,725*10,000). Similarly, in the second paragraph, the first sentence contains exposure keywords, which contributes to the total scaled exposure measure by 4.05 (1/2,469*10,000). The third paragraph is a control with no climate-related keywords, which is why our scaled measure is 0.

Table 3 shows the distribution of our climate textual measures. The 419 financial documents have an average of 11 *exposure* sentences and 18 *adaptation* sentences. These translate to a scaled textual measure of 46 and 92, respectively. Hereafter, we refer to the scaled measure as our textual measures. Budgets have the highest textual measure of 144 for *exposure* and 69 for *adaptation*. This is followed by CAFR, with a textual measure of 55 for *exposure* and 31 for *adaptation*. Bonds have the lowest textual measure of 15 for *exposure* and 18 for *adaptation*.

One interesting observation from untabulated analysis is that fewer than 10 percent of the documents have no mention of the exposure or adaptation keywords. In fact, when we aggregate to a city-level, all cities have discussed climate exposure and adaptation actions in their financial disclosures at some point. This finding highlights the importance of the climate issues faced by cities.

3.4 Measurement validation

Comment for the reviewer: In what follows, we describe the preliminary measurement validation using our pilot study. In a full study, we will replicate these steps on a larger sample.

We take two steps to validate that our climate disclosure measures pick up meaningful variation in a city's climate risk exposure and adaptation.

We start by running descriptive analyses on our textual measures in relation to actual climate risks. We plot the textual measures over time, and expect an increase after climate events like hurricanes. In the full analysis, we will be able to validate the timing of our textual measures by exploiting the staggered timing of hurricanes in different states. For example, Nagar and Schoenfeld (2021) shows that there are 22 storms with at least $2 billion in damage to a number of states from 2003 to 2019. In Florida, where we conduct our pilot analysis, Nagar and Schoenfeld (2021) shows that the first storm in our sample is Hurricane Matthew, which caused 6 deaths in October of 2016 (ABC News, 2016). Thus, we expect an increase in our textual measures after 2016.

Figure 1 plots the average number of sentences in a document that have exposure and adaptation keywords over time. We split cities by flood risk, where a high flood risk indicates cities with an above median flood risk. Consistent with our expectation, the number of sentences for climate exposure and adaptation are mostly stable between 2013 and 2015; the number begins to gradually increase for high flood risk cities in 2016. Comparing the types of financial disclosures, we see that budgets contain the most information and variation, with an average of 12 sentences on climate exposure in 2013 and 20 sentences in 2018. Bonds start with almost no disclosure information in 2013, but the number of relevant sentences begins increasing after 2016 and hits 20 in 2018 for cities with high flood risk. In contrast, disclosure information in CAFR remains low over the years.[6]

For the full sample, we will also be able to leverage the variation in flood risk across states to validate our textual measures. **Figure 2** plots our textual measures by state, where states with a higher flood risk are ranked at the top. Currently only Florida is filled in, but when we have more data, we expect a higher textual measure for states with a higher flood risk.

We also run a difference-in-differences analysis to compare our textual measure for cities with

[6]The figures show high mentions of exposure and adaptation for bonds than CAFR, but because there are on average more sentences in bonds, the scaled textual measures are lower in bonds than in CAFR.

low and with high flood risks. Low flood risk cities serve as the control. We expect that after a hurricane, cities with a high flood risk will have a higher textual measure than will those in the control group. Specifically, we test:

$$\textit{Textual Measure}_{it} = \beta_1 \textit{High Flood Risk}_{it} \times \textit{Post}_{it} + \beta_2 \textit{Post}_{it} + \beta_3 \textit{Population}_{it} + \beta_4 FE + \epsilon_{it} \qquad (2)$$

where $TextualMeasure_{it}$ is the textual measure for municipality i at time t. We separately look at the textual measures for exposure and adaptation. *High Flood Risk*$_{it}$ is an indicator that equals 1 if the city's flood risk is above the median, or belongs to the upper quartile, depending on the specification. *Post*$_{it}$ is an indicator that equals 1 for observations starting in 2017. Conceptually, we expect our textual measure to increase after the impact from Hurricane Matthew in October 2016. We control for the size of the cities by including $Population_{it}$, which is the logarithm of annual population from Muni Atlas. We include city-times-report-type fixed effects to control for time-invariant differences in the textual measures for each city's reports. We cluster standard errors by city to address any potential correlations between different observations in a city.

Table 4 Panel A shows the results from estimating equation (1). Columns 1 and 2 show the results comparing cities from the top and bottom quartiles of flood risk, while Columns 3 and 4 show the results comparing cities from the top and bottom half of flood risk. In Columns 1 and 3, where *exposure* is the outcome variable, the coefficient on the interaction between *High Flood Risk* and *Post* is positive and statistically significant. Using the specification in Column 3, this magnitude translates to a 54 $(24.95/45.91)$ percent increase in *exposure* for cities above the median flood risk after 2016. This result provides validation that our measure for climate risk exposure correlates with the occurrence of flood-related natural disasters. Columns 2 and 4 show the results for *adaptation*, and the coefficient on the interaction term is positive, but only statistically significant

when comparing the top and bottom quartile. This is not surprising, given that some cities that face climate exposure may not take adaptation actions, and that this is less likely to be the case for cities in the highest flood risk quartile.

Applying the power analysis discussed in Section 2.3 to this difference-in-differences specification, the minimum detectable effect size for exposure and adaptation based on a sample size of 18,081 is 1.20 and 1.93, respectively. Both are much smaller than our detected effect in this pilot study, providing comfort that we will have sufficient power to conduct this validation test in the full sample.

Our second validation test correlates our measure of adaptation with the expenses that cities spend on the infrastructure for mitigating flood risks. One key assumption in the creation of our climate risks measure is that disclosures about climate adaptation reflects actual actions. In other words, if cities engage in cheap talk, then our measure of adaptation may be misleading. To mitigate this concern, we correlate our textual measure of *adaptation* with a city's expenses from capital improvement and emergency-related funds. We assume that if a city invests more in adaptation action, the city will also have higher expenses in subsequent years. Further, we believe this assumption is particularly true for municipal budgets, which should reflect true action because they contain forward-looking information on how the city plans to allocate money. As an example, Appendix A shows an extract from Tampa's 2018 budget, where the city allocates $9 million over five years to a stormwater improvement project for flooding relief. These budget disclosures are part of a Capital Improvement Plan ("CIP"), which are required in most states for the planning of long-term infrastructures investments (Elmer, 2005).

Table 4 Panel B regresses our textual measures on the relevant fund expenses in the year t+1. We use expenses that belong to a capital project or an emergency fund in the Muni Atlas data.[7]

[7]We use funds that contain the following keywords in the fund name: capital project, capital improvement, disaster

Because of the limited number of cities with relevant fund expenses, and because the Muni Atlas fund-level data starts in 2017, we only have 71 observations in the pilot study, and the coefficient on the fund expense is only marginally statistically significant in all documents, and is only statistically significant at a 15% level for budgets. However, the magnitude for *adaptation* is positive and larger than the magnitude for *exposure*, which we do not expect to be correlated with fund expenses.

Given the small sample, a power analysis will help gauge the power of the test with the full sample. For all documents, the minimum detectable effect size for exposure and adaptation is 1.20 and 1.93, respectively, which are comparable to the observed effect in the pilot test. However, the minimum detectable effect size for exposure and adaptation in budgets is 3.49 and 5.72, respectively. While these are larger than the observed magnitude in this pilot, they represent a change of five (3.49/68.75) and four (5.72/144.37) percent, respectively.

Given the observation that cities disclose the most climate-related information in budgets, and that adaptation actions are most likely realized in future budgets, in subsequent analyses, we show the results for textual measures as a sum of all three document types and for budgets alone. In other words, we focus on four variables: exposure and adaptation for all documents, and exposure and adaptation using budgets.

3.5 Other validation and sensitivity analyses

We conduct a battery of additional validation and sensitivity tests to enhance the accuracy of our textual measures.

First, we cross check our textual measures with the observations from manually reading a sample of documents. In the pilot study, we manually examine the disclosure trends in five Florida cities: Fort Lauderdale, Miami, Miami Beach, Orlando, and Tampa. This initial reading is done

relief, emergency.

without referencing the textual measures to guarantee an independent assessment of disclosure patterns. We then compare results from the manual process with our textual measures, and evaluate the reason for any differences in order to refine our measure. We will repeat this process until the textual measures align with or capture better patterns than the manual reading.

This process yields three sets of observations. First, in some cases, we find keywords that should be added to or removed from the dictionary. For example, we observed the use of "tidal control valves" (in addition to "tidal valves"), and added this to the keywords list. Second, there are patterns that are observed by the human eye but that are not captured by word counts. For example, when reading the documents, we observe that climate disclosures are placed higher in the document over time, which reflects a higher emphasis on climate change. Thus, we create a measure that weights disclosures by their position in the document, where an earlier disclosure gets a higher weight. Third, the textual measures sometimes capture patterns missed by the human eye. These mostly happen because there are limits to the number of keywords a human can search for when reading through the documents.

Because of these observations, in our full analysis, we will include two additional variants of the textual measures in order to quantify other dimensions of the disclosure. First, we quantify how concentrated or sparse the climate-related disclosures are by examining the number of groups, where a group is defined as two or more distinct climate-related keywords within five sentences. This allows us to separate reports that discuss climate change in one large section from reports that mention climate change in smaller segments. Appendix B includes a preliminary figure showing the number of groups over time. Second, we create a measure that weights sentences by their position in the report, where sentences that are higher in the document are given a higher weight. This allows us to distinguish reports that disclose climate change early in a report, in the main body, and in the appendix. Appendix C includes a preliminary figure showing the weighted sentences

measures over time.

Second, 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. Appendix D plots the total number of climate-related keywords in the document over time and by flood risk. The overall trends are similar to the plot using adaptation and exposure sentences in **Figure 1**. Our second sensitivity analysis examines the assumptions used in creating the groups of text. While we define a group as two or more distinct keywords within five sentences, in Appendix E, we 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.

Finally, we plan to complete a falsification analysis with a placebo dictionary of words that are unrelated to climate risks. We will then repeat our main analysis with a placebo textual measure that we intend to create using the placebo dictionary. If our main variables capture information about climate risks, our placebo measure should not have significant results in our main analysis. One potential placebo dictionary is for non-flood hazards, such as drought and extreme weather. Appendix F shows the average sentences containing different types of hazards keywords in our Florida pilot sample. Consistent with the notion that Florida face more flood risks after 2016, only sentences containing meteorological (e.g., hurricane) and hydrological (e.g., flood) hazards spike after 2016, and the other hazard types remain flat. Also, consistent with flood risks being the main climate concern in Florida, sentences containing climatological (e.g., drought and wildfire) and geophyiscal (e.g., avalanche) hazards are close to zero.

4 Determinants of Climate Adaptation

After establishing that our textual measures pick up meaningful variation in cities' exposure and adaptation to climate risks, we use these measures to understand the variation in climate risk preparedness. To examine these determinants, we run the following regression:

$$\textit{Textual Measure}_{it} = \beta_1 \textit{Determinants}_{it} + \beta_2 \textit{High Flood Risk}_{it} + \beta_3 \textit{Population}_{it} + \beta_4 FE + \epsilon_{it} \quad (3)$$

where $\textit{Textual Measure}_{it}$ is the textual measure of climate risks for municipality i at time t. As discussed in Section 3.4, our dependent variables are the exposure and adaptation measures extracted from all financial disclosures, and from city budgets. $\textit{Determinants}_{it}$ is a binary variable that captures one of our four determinant variables, which we explain in subsequent subsections. We control for the city's flood risk and population size. $\textit{High Flood Risk}_{it}$ is an indicator that equals 1 if the city's flood risk is above the median. $Population_{it}$ is the logarithm of the city population. We include state-year fixed effects to control for time-variant changes in each state's climate risk (in this pilot study, we include only year fixed effects as we are only examining cities in one state). We cluster standard errors by city to address any potential correlations between different observations in a city.

For these determinant tests, we conduct power analysis to estimate the minimum detectable effect size based on assumptions discussed in Section 2.3. Assuming a sample of 6027 city-year observations, for *exposure*, the minimum detectable effect size is 2.07 for all documents, and 3.49 for budgets. For *adaptation*, the minimum detectable effect size is 3.34 for all documents, and 5.72 for budgets.

To study the relevant determinants, it would be best to compare cities with similar characteris-

tics. While we do control for the level of flood risk and population size in our regressions, as an alternative specification in the full analysis, we will match cities on flood risk and population using Coarsened Exact Matching ("CEM"). We will then repeat the main regressions with CEM-matched cities, and will include CEM strata fixed effects to compare cities within each CEM strata.

Comment for the reviewer: In the following sections, we describe the preliminary results using our pilot study. In a full study, we will replicate these steps on a larger sample.

4.1 Political affiliation

The existing literature shows that partisanship can shape beliefs as well as real economic decisions (Gerber and Huber, 2010; Dagostino et al., 2020; Kempf and Tsoutsoura, 2020). There is evidence that public views of climate change are influenced by party affiliation (e.g., Palm et al., 2017), and that even the words "climate change" can be politically charged (Nagar and Schoenfeld, 2021). If Republicans place a lower probability on climate hazards due to their political affiliation, then we should observe lower adaptation for cities with Republican mayors.

Diligent city managers, however, are required to plan ahead and invest in adaptive measures, especially in areas with a high flood risk. If political affiliation does not change climate-change risk assessment, but merely change the use of terms like "climate change," we expect to observe no difference in climate adaptation between Democratic and Republican cities. Thus, it is an empirical question whether there is a difference in adaptation between Republican and Democratic cities.

To run our political affiliation tests, we use the data on mayoral political affiliation from OurCampaigns.com. We augment these data with manually collected information for city-years where the mayor or her political affiliation was not found on OurCampaigns.com. **Table 3 Panel B** shows that among the 419 city-year observations, 201 have a Democratic mayor, 137 have a Republican mayor, and 81 have mayors that are neither Republican or Democratic. Since our main prediction

is that Republican mayors invest less in adaptation, we group the non-affiliated mayors with the Democratic mayors.

Figure 3 Panel A plots the textual measures in separate time series for cities with Republican and with Democratic mayors, and for cities above and below the median flood risk. Similarly to the results in **Figure 1**, we observe an increase in *exposure* and *adaptation*, but only for cities with both a high flood risk and a Democratic mayor. The adaptation measure for cities with low flood risks and for cities with Republican mayors remain flat over the years, even after the hurricane seasons in 2016 and 2017.

Table 5 shows the results from running regression (2), where one of the $Determinants$ variable is *Republican*, defined as cities with a Republican mayor. Columns 2 and 4 show the effect on *adaptation* in budgets and in all documents, respectively. In both specifications, the coefficient on *Republican* is negative and statistically significant. Using the specification in Column 2, this suggests that cities with Republican mayors have a lower *adaptation* of 55 $(79.82/144.37)$ percent.

We observe a similar decrease in climate exposure measures in cities with Republican mayors in Columns 1 and 3. Using the specification in Column 1, this suggests that cities with Republican mayors have a lower *exposure* of 45 $(30.74/68.75)$ percent. This result is consistent with Republican mayors placing a lower concern for flood risks and investing less in adaptation.[8][9]

4.2 Public opinion

Our second determinant is public opinion about climate change. Like party affiliation, public opinion reflects the city's belief about climate change. Local residents with a higher concern for climate change would want their city to engage more in climate adaptation. If city officials repre-

[8] In untabulated analysis, we repeat this regression with textual measure of keywords that directly reference climate change, and the effects are even stronger than that of using flood hazards keywords in our exposure variable.

[9] We acknowledge that this result shows that our climate exposure variable not just captures exposure to flood risks, but is also affected by political affiliation. However, we do not think the same applies to our adaptation measures, since even Republican mayors will disclose about their adaptation actions and allocate funding for these actions in budgets.

sent the local residents, then we expect cities where the people have a higher concern for climate change to have a higher *adaptation*.

However, there is mixed evidence in the literature on how accountable local officials are to the voters' interest (e.g., Besley and Case, 1995; List and Sturm, 2006). List and Sturm (2006) finds that local environmental groups can affect environmental policy, but it depends on the size of the environmental groups, term limits and the competitiveness of elections. As such, it is an empirical question whether local residents' opinion about climate change is a determinant of a city's climate adaptation.

To test for this determinant, we use the 2020 Yale Climate Opinion Survey data, which captures beliefs about climate change at the state, congressional district, and county levels in the US. In our pilot tests, we use the county-level responses to the following prompt to capture people's concern about the local 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 create an indicator *Local Officials Should Do More above median* for cities where this measure is above the median. One caveat about using this data is that it does not ask specifically about flood risks. People expressing concerns about global warming in this survey may want local governments to help lower carbon emissions instead of investing in local flood adaptation. In the full study, we will explore other prompts in this survey to try and tease out how people are concerned about global warming.

Figure 3 Panel B plots our textual measures in separate time series for cities above and below the median public opinion, and for those above and below the median flood risk. For *exposure*, the trend for all groups is a gradual increase after 2016. While we only expect an increase for cities with high flood risks, in our Florida sample, even cities below the median flood risk face threats

from hurricanes. Interestingly, we observe a higher adaptation in recent years for high-flood-risk cities with a lower public opinion on climate change. One potential reason for this result is that the survey was administered in 2020, and residents feel more trust in their local governments in cities where adaptation was high recently.

Table 5 shows the regression result for the determinants analysis. Columns 2 and 4 show the effect on *adaptation* in all documents and in budgets, respectively. The coefficient on *Local Officials Should Do More above median* is positive and statistically significant, suggesting that cities where people that are concerned about climate change are investing more in flood adaptation. We do not observe the same increase in climate exposure measures. In Columns 1 and 3, the coefficient on the interaction term is positive, but not statistically significant. The magnitude is also smaller than the magnitude for *adaptation*.

4.3 Credit constraint

Our third determinant examines if credit constraints explain why some high-risk cities do not invest in adaptation. Among cities that voluntarily disclose climate change information in the CDP survey, 43% did not have an adaptation plan, and 25% cite budgetary capacity issues as a barrier (CDP, 2021). Tackling climate risks is costly; according to the CDP survey, an average climate project costs $63 million. Thus, we expect cities with limited funding and credit to invest less in climate adaptation. On the other hand, cities are not alone in combating climate change. Federal agencies like FEMA provide funding opportunities to invest in adaptation. For example, FEMA's Pre-Disaster Mitigation program provide funding for communities to invest in adaptation infrastructure. If cities can utilize FEMA funding, then we do not expect credit constraint to correlate with climate adaptation.

We measure credit constraints using the outstanding debt per capita from Muni Atlas. However,

the interpretation of debt in relation to credit constraint is debated in the literature (Farre-Mensa and Ljungqvist, 2016). On the one hand, cities with a lower level of debt has less leverage, and hence may be able to borrow more to fund adaptation projects. On the other hand, these cities may have a lower debt because they are face credit constraints and are not able to borrow more. In fact, some cities with high outstanding debt may have been using the debt to fund climate adaptation projects. Thus, it is not clear how a city's debt per capita correlates with our *adaptation* measure.[10]

Figure 3 Panel C plots the textual measures in separate time series for cities above and below the median debt per capita, and for cities above and below the median flood risk. For *exposure*, all groups gradually start increasing after 2016. While we only expect an increase for cities with high flood risks, in our Florida sample, even cities below the median flood risk face threats from hurricanes. For *adaptation*, the trend is less clear than for other determinants, it appears that cities with high debt per capita has lower *adaptation* in the earlier years, and show gradual increase after 2016, while cities with low debt per capita remain relatively flat over the years. In the determinants regression in **Table 5**, the coefficient on *Total Debt per Capita above median* is negative, but not statistically significant except for *adaptation* in budgets. This result may suggest that credit constraint is not correlated with *adaptation*, which would be an interesting observation given the responses from the CDP survey. However, these results may stem from a lack of power and from limitations in the measurement.

4.4 Capital budget outlook

Our final determinant is the planning horizon in a city's capital budget. Local governments have different budget time frames (e.g., one year, five years, or even ten years). Since climate risk is a long-term risk, if budget time frames affect the city's planning horizon, then cities with a shorter

[10] In the full analysis, we will incorporate more data and additional measures to study credit constraints. For example, we will follow Nakhmurina (2020) and include a proxy for fiscal health that uses the ratio of general revenue to net expenses. Conceptually, this ratio is higher for cities that can better control and manage their expenses.

budget outlook may not incorporate climate risks in their decision-making. As such, we expect that local governments with a longer capital budget outlook are more likely to invest in adaptation for climate change.

This idea is similar to that of corporate myopia, where more frequent and short-term financial disclosure cause managers to make myopic decisions, such as under-investing in long-term capital expenditure (Gigler et al., 2014; Nallareddy et al., 2017; Kraft et al., 2018). However, prior literature in this corporate setting finds mixed results. Nallareddy et al. (2017) find that mandatory quarterly reporting in the UK has no impact on firm's capital investments, while Kraft et al. (2018) find that the staggered introduction of more frequent reporting in the US is associated with a decline in capital investments. Thus, in the municipal setting, it is an empirical question whether a longer capital budget outlook is associated with more adaptation investment in long-term climate risks.

To capture a city's budget outlook, we manually collect the number of years presented in a city's capital budget plan. For most documents, we can identify this information using the number of years in the budget tables. Many cities also explicitly label their capital budget outlook using terms like "five-year Capital Improvement Program". The average city in Florida has a capital budget outlook of four years, whereas the median is five years.

Figure 3 Panel D plots the textual measures in separate time series for cities above and below the median capital budget outlook, and for cities above and below the median flood risk. For *exposure*, all groups, except those with low flood risk and low outlook, start gradually increasing after 2016. For *adaptation*, cities with a high capital budget outlook engage in more adaptation after 2016, but those with a low capital budget outlook remain flat.

Table 5 shows the regression results for the determinants analysis, where the indicator *Capital Budget Outlook above median* captures cities with an above median capital budget outlook. In this

pilot study, the coefficient on *Capital Budget Outlook above median* is not statistically different from zero in all specifications. One reason for this result is that there is a lack of variation in the capital budget outlook in Florida, where the majority of cities have an outlook of 5 years due to of a state-level requirement. In the full analysis, we hope to exploit variations in state-level regulations in capital budget outlooks.

5 Market Pricing of Climate Risks

In this section, we use our textual measures to reexamine whether climate risks are priced in the municipal bonds market. While prior research finds evidence that local governments with higher threats from the rise in sea level also experience a higher financing cost (Painter, 2020; Goldsmith-Pinkham et al., 2021), whether climate risk and adaptation are priced in the municipal bonds market remains an empirical question for various reasons. First, if state and federal agencies such as FEMA provide funding to "bail out" the cities affected by climate hazards, then we would expect climate risk to have a smaller pricing effect on municipal bonds. Second, it is possible that information about adaptation in a city is not yet incorporated in the pricing of municipal bonds, which is less liquid than the pricing for corporate bonds.

Additionally, prior literature measures climate risk based mostly on geophysical information, with some adaptation assumptions. Painter (2020) uses a measure of climate risk from Hallegatte et al. (2013), which estimates the impact from the rise in sea level using adaptation assumptions that are partly based on author estimates. Hallegatte et al. (2013) acknowledge that their defense level is based on limited information, and they call for more research to improve the measure. Goldsmith-Pinkham et al. (2021) 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.

Compared to these studies, we believe our measures (especially the adaptation measure) better measure true flood risk, which is affected by geophysical conditions and by a city's adaptation efforts. Additionally, our measure captures flood risk regardless of whether the city is located on the sea coast. Recent events have shown that flood risk can be significant for the cities located on river banks and those that do not have good drainage systems.[11]

We first replicate the methodology in Painter (2020) and (Goldsmith-Pinkham et al., 2021), and then we include our textual measures to study how adaptation is priced in the municipal bonds market. To begin with, Painter (2020) studies how climate risk affects the issuance cost of municipal bonds using primary market data. We use the data on bond issuances from Mergent Municipal for this analysis. Following Painter (2020), we estimate the following regression:

$$\text{Issuance Cost}_{it} = \beta_1 \text{Climate Risk}_{it} + \beta_2 X_{it} + \beta_3 FixedEffects + \epsilon_{it} \tag{4}$$

where Issuance Cost_{it} is the sum of the annualized gross spread and the offering yield for bonds issued by municipality i at time t in Painter (2020). As we are currently missing data for gross spread, we use offering yield and offering spread, defined as the difference between offering yield and the maturity-matched yield from the treasury curve. Climate Risk_{it} is our textual measures for exposure and adaptation, as well as the flood risk measure from the First Street Foundation. In the full analysis, we will try to obtain and include the measures for sea level rise used in Painter (2020) and (Goldsmith-Pinkham et al., 2021). X_{it} is a vector of controls. Following Painter (2020), 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

[11] See, for example, *Climate change blamed for devastating German floods*, Financial Times, July 16, 2021; and *China flood death toll rises to 33, stoking its climate change concerns*, Financial Times, July 22, 2021.

for whether the bond is callable, insured, sinkable, pre-refunded, funded by general obligation and competitively issued. We do not control for whether the bond is federally tax-exempt, state tax-exempt, or subject to AMT because our data lacks variation in these variables. We include state-year fixed effects to control for time-variant changes in issuance costs in each state (in this pilot study, we include only year fixed effects as we are only examine cities in Florida). We cluster standard errors by city to address potential correlations between different observations within a city.

We expect β_1 to be positive and significant for measures of climate risk exposure, but negative and significant for measures of adaptation. Our hypothesis is that cities with a higher climate risk exposure also pay a higher issuance cost to compensate investors. We also hypothesize that cities with high adaptation measures can mitigate some of the heightened issuance cost since adaptation reduces climate risks. Conceptually, higher climate risks translate to a higher probability of a bond being affected by losses from adverse climate events. A recent example is the effect of Hurricane Maria that hit Puerto Rico in September of 2017 and which caused severe flooding and damage. In the subsequent month, Moody downgraded the ratings of securities from four issuers in Puerto Rico (Moody's, 2017b).

Table 6 shows the results from our replication of Painter (2020). Columns 1 to 2 uses offering spread as the dependent variable, and Columns 3 to 4 uses offering yield as the dependent variable. When we only include the flood risk measure in Columns 1 and 3, the coefficient on *Flood Risk* is negative but only statistically significant for offering spread. This negative result is a little puzzling, but may also be attributable to our small sample of Florida cities, where even cities with low flood risk face considerable threat from hurricanes. When we include our textual measures in Columns 2 and 4, the coefficient on *Adaptation* is negative but not statistically significant. The direction of the result is consistent with cities with higher adaptation are perceived as less risky. The coefficient

on *Exposure* is positive and significant, which is consistent with the market pricing in the climate risk exposure. Note that the number of bond observations in this analysis exceeds the number of bond prospectuses collected (see Table 1). This is because each municipal bond issue has multiple bonds and only one bond prospectus.

Applying the power analysis discussed in Section 2.3 to the market pricing tests, the minimum detectable effect size for offering spread and offering yield is 0.01 and 0.03, respectively. We calculate this based on an estimated sample size assuming the full sample have the same proportion of bond issuance as those in Florida. In the full study, we will try to further increase the power of this analysis, such as by only examining cities with high flood risk.

Next, we replicate (Goldsmith-Pinkham et al., 2021), which studies how climate risk affects yield in the secondary market for municipal bonds. Following (Goldsmith-Pinkham et al., 2021), we use the historical transaction price data from the Municipal Securities Rulemaking Board ("MSRB"), and estimate the following regression:

$$\text{Spread}_{it} = \beta_1 \text{Climate Risk}_{it} + \beta_2 X_{it} + \beta_3 FixedEffects + \epsilon_{it} \tag{5}$$

where Spread_{it} is the volume-weighted average credit spread of a municipal bond issued by municipality i at time t. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the treasury curve. Climate Risk_{it} is our textual measures for exposure and adaptation, as well as the flood risk measure from the First Street Foundation. X_{it} is a vector of controls, following (Goldsmith-Pinkham et al., 2021), 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.

We include trade-month fixed effects to control for time-variant changes in the spread. We cluster standard errors by city and year-month.

Table 7 shows the results from our replication of (Goldsmith-Pinkham et al., 2021). When we only include the flood risk measure in Columns 1, the coefficient on *Flood Risk* is positive but not statistically significant. In Column 2, when we include our textual measures, the coefficient on *Adaptation* is negative and statistically significant, and the coefficient on *Exposure* is negative and statistically significant. This result is consistent with the market requiring a higher return for holding bonds with a higher climate risk exposure and adaptation mitigating this risk exposure (but to a smaller extent). Power analysis shows that with the full sample, we should be able to detect a minimum effect size of 0.006. While this effect size is smaller than our observed effect on *Exposure*, it is still larger than our observed effect on *Adaptation*. In the full study, we will try to further increase the power of this analysis, such as by only examining cities with high flood risk.

6 Potential Challenges and Additional Analyses

Comment for the reviewer: In this section, we describe potential challenges we may face for the full sample during data collection, textual processing, and results analysis. We also propose analyses we can run to address some of these concerns.

6.1 Potential challenges with data collection

This project involves the manual collection of a new set of data from municipality websites, and we foresee a few potential issues during the collection process. First, while the public disclosure of CAFRs, budgets, and bond prospectus are mandatory, not all of these documents are readily accessible. Second, the quality of these reports can also be a concern if local governments do not provide adequate detail.

To address these concerns, we focus on larger population cities. Larger cities tend to have more

requests for information, which means that the reports are more likely to be available online. Reports for these cities are also likely of higher quality due to the higher demand and because of the additional resources available for their creation.[12] When reports are not online, we will decide on the size of a reasonable sample and will manually request the reports. In the Florida sample, after online searches and contacting city officials directly, only 9 out of the 420 budgets, and 8 out of the 420 CAFR were unavailable, which is not a significant number and provides comfort on the completeness of our data.

6.2 Potential challenges for textual processing

There may be challenges in applying our climate dictionary to documents. One challenge is the variation in the choice of words, where cities use different words to capture similar concepts related to flood risk or adaptation. Thus, as we expand to the full sample, we will randomly select a diverse set of reports to manually read through. Furthermore, as there may be overfitting for the samples where we manually choose the keywords, we will include a robustness analysis that excludes these cities. Additionally, we may choose some cities that are known for their climate adaptation but that are not in our sample as an out-of-sample group to identify the relevant keywords.

Another challenge is deciding the boundary of our dictionaries. In our current analysis, we focus on climate risks related to flood events, such as hurricanes and the sea level rise. This narrow but focused definition allows us to measure risk and adaptation actions more precisely. We do not include keywords that relate to greenhouse gas or to other natural disasters like drought and extreme temperatures. We will reconsider this boundary based on the feedback we will receive from the conference participants and as we learn more institutional details about other climate risks that are more pertinent in other regions as we expand to the full sample.

[12] In the Florida sample, the total number of sentences in a report is significantly positively correlated with the population of the city.

Additionally, we may experience other challenges in applying textual analysis to documents that vary in formats. For example, if some states require a different format for budgets, we will have to customize our textual analysis method to ensure the comparability of our textual measures. We will continuously improve our codes, and suggestions from the conference participants can help to establish a textual analysis methodology that accurately captures climate risk exposures and adaptation.

6.3 Potential challenges for regression analyses

One challenge with using textual measures is deciding the scaling. Document sizes vary across years, cities, and document types. To ensure comparability, we currently scale our textual measures by the total number of sentences. This assumes that in order for our textual measure to remain stable over time, cities will proportionally increase the length of their climate disclosures with the length of their documents. We will manually examine this assumption in more detail, and if the newly added texts are mostly unrelated to climate risks, we will consider the use of two alternatives: first, we may use the total number of sentences that include our keywords without scaling; second, to ensure comparability across cities, we may scale by the average total sentences of each city-document type.

Another potential issue in our regression analyses is that we may not observe sufficient variation in certain determinant variables. One such example is the budget horizon in Florida, where the majority of the cities in our sample have a five-year horizon due to the state-mandated rule that CIPs should have a minimum of five years starting in 2017. While this is a challenge in our pilot study, it can be an opportunity if different states have a different minimum, or if state rules have a staggered implementation. If there is a staggered timing, we can exploit the change in the budget horizon from changes in state rules to examine the effect of the planning horizon on climate preparedness. If there is still a lack of variation in the budget horizon of the full sample, we will consider other

proxies.

7 Conclusion

Our paper leverages a textual analysis of local governments' financial reports to create a novel measure for a city's climate preparedness. As climate change increases the severity and frequency of extreme weather events, it is critical to understand cities' adaptation strategies. We shed light on this topic using a city's financial disclosures, and focus on how cities budget for capital improvement projects aimed at lowering the impact from flood risks.

With a full sample, we will be able to examine how party affiliation, public opinion about climate change, credit constraints, and the budget planning horizon all help explain a city's climate preparedness. Furthermore, we will be able to re-examine how the municipal bond market prices climate risks as well as cities' adaptation measures.

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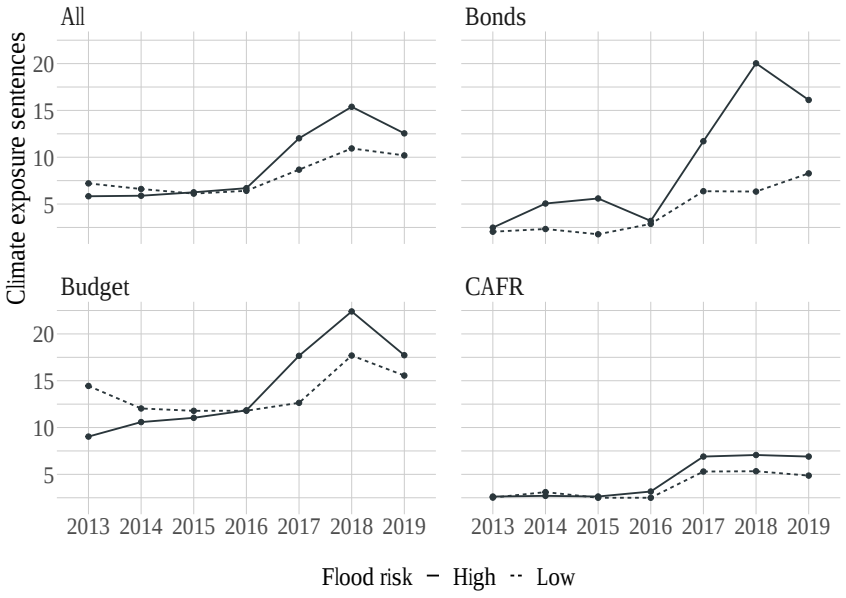
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Figure 1: Climate disclosure and adaptation measures over time and by flood risk.
This figure presents climate disclosure and adaptation measures in all documents, budgets, CAFRs, and bond prospectuses over the sample period, 2013-2019. The solid line 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-median percentage properties at risk, and low-flood risk cities have below-median percentage properties at risk. Panel A plots exposure sentences. Panel B plots the adaptation sentences. *Note:* the number of adaptation sentences in bond prospectuses issued by low flood risk cities spikes in 2017 because in that year West Palm Beach and Miami Beach together issued three bonds to refund adaptation-related projects.

Panel A: Climate Exposure



Panel B: Adaptation

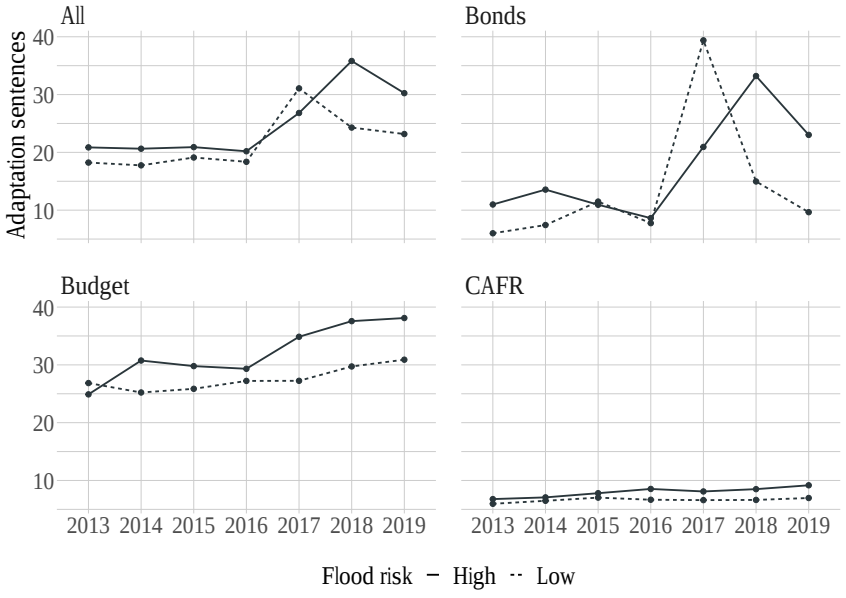


Figure 2: Climate disclosure and adaptation measures by state.
This figure plots the climate disclosure and adaptation measures across states. The points represent the mean number of sentences, scaled by total number of sentences in a document, while the bars represent the standard deviation. States on the vertical axis are ordered such that the percentage of properties with flood risk decreases from top to bottom. Panel A plots the climate exposure sentences. Panel B plots the adaptation sentences.

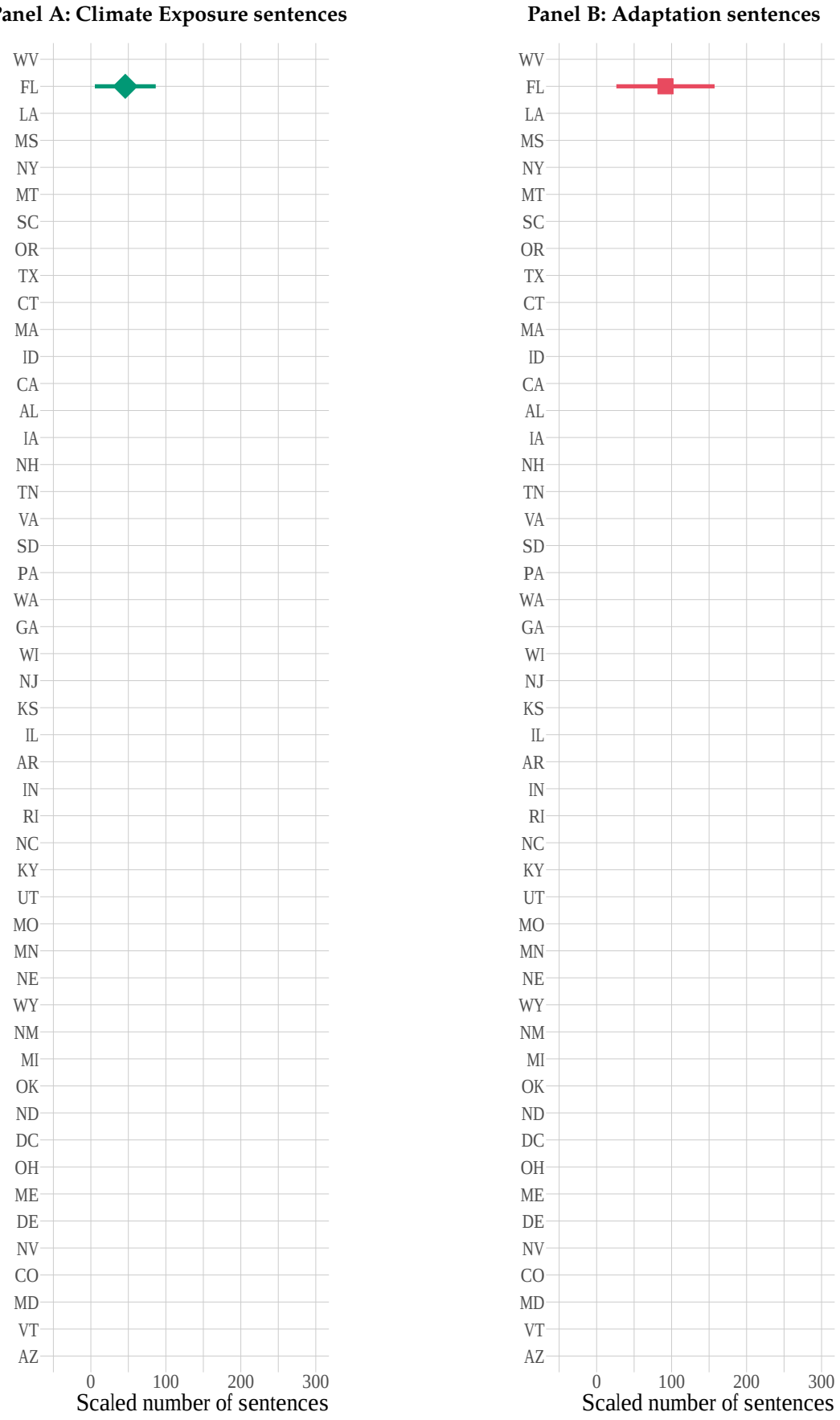
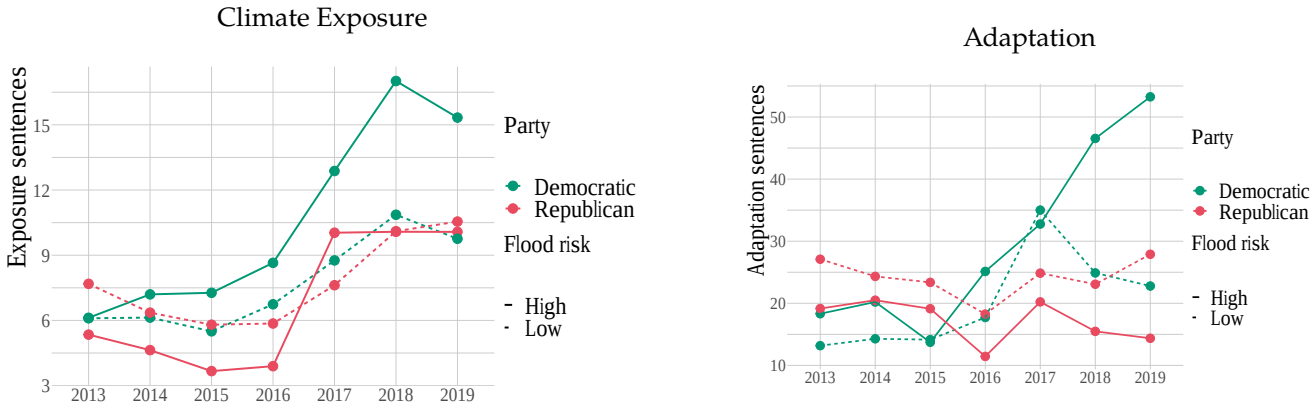
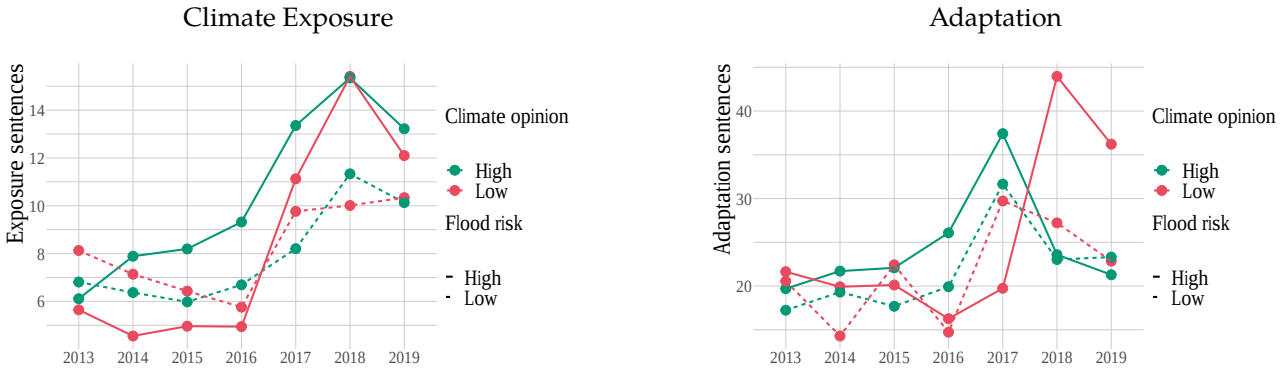


Figure 3: Climate exposure and adaptation over time and by flood risk.
This figure presents climate disclosure and adaptation measures in all documents over the sample period, 2013-2019. The solid line depicts the trends for high flood risk cities, and the dashed line shows the trends for low flood risk cities. High flood risk cities have above-median percentage properties at risk, and low-flood risk cities have below-median percentage properties at risk. Panel A plots exposure and adaptation sentences by political affiliation. Panel B plots exposure and adaptation sentences by climate opinion, i.e., by whether the public believes that local officials should do more to address global warming. Panel C plots exposure and adaptation sentences by debt per capita. Panel D plots exposure and adaptation sentences by the length of capital budget oulook.

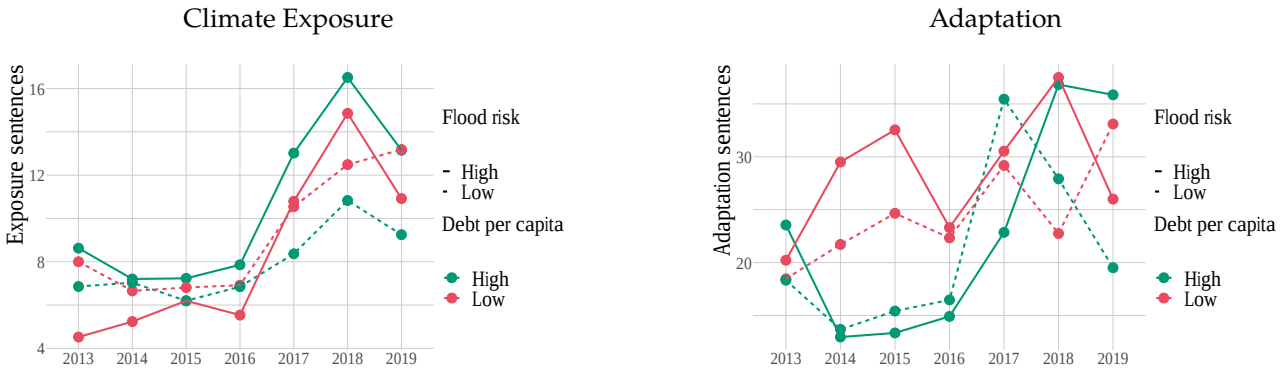
Panel A: Political affiliation



Panel B: Climate opinion



Panel C: Credit constraint



Panel D: Capital budget outlook

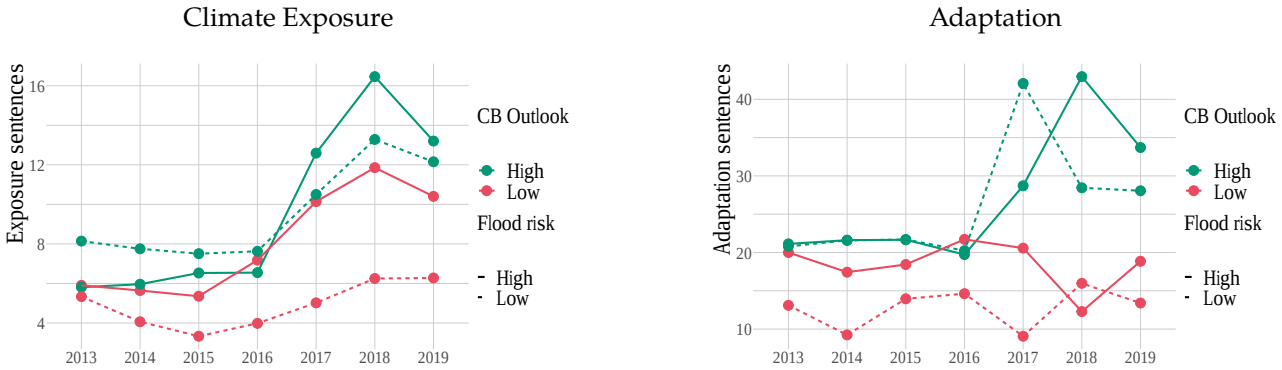


Table 1: Sample composition by state.
The sample comprises the cities with flood risk data from First Street Foundation, financial data from Muni Atlas, and the 2010 U.S. Census population of over 40,000 people. This selection procedure yields 861 cities in 48 states and the District of Columbia for a period spanning 2013-2019. 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*. We obtained the collected documents by searching individual city websites, EMMA, Wayback Machine, and contacting city officials. *Note:* For our Florida pilot study, we collected 411 budgets and 412 CAFRs from 60 cities over time, with 9 budgets and 8 CAFRs missing because the cities could not provide these documents to us. The number of budgets which we can use in our data went down to 397, because 14 budgets were comprised of tables and did not contain meaningful information. We collected 295 bond prospectuses. Because some cities issue multiple bonds per year, this amount translates into 154 city-year bond observations.

State	N Cities	Population	Properties at risk, %	Properties at risk, total	N Budgets	N CAFRs	N Bond prospectuses	Collected
AL	10	118,280	9.71	10,838				
AR	9	79,626	7.11	3,969				
AZ	20	215,379	2.79	1,491				
CA	184	139,166	9.72	4,526				
CO	19	142,399	3.90	2,731				
CT	13	87,426	10.48	2,538				
DC	1	602,723	5.30	7,300				
DE	1	70,851	4.28	1,494				
FL	60	109,568	23.79	15,744	397	412	295	✓
GA	13	112,338	7.92	6,672				
IA	11	84,493	9.63	3,975				
ID	8	75,986	9.82	5,337				
IL	41	136,045	7.12	4,211				
IN	20	75,269	6.80	3,508				
KS	11	117,726	7.23	4,471				
KY	4	112,944	6.35	3,662				
LA	8	133,648	20.54	14,626				
MA	31	88,774	10.27	2,458				
MD	5	172,414	3.42	4,286				
ME	1	66,194	4.86	1,511				
MI	29	100,499	5.49	3,228				
MN	20	91,562	6.04	2,544				
MO	15	118,346	6.16	5,443				
MS	6	70,247	15.05	5,977				
MT	3	76,488	12.78	5,079				
NC	21	149,606	6.51	5,914				
ND	4	65,137	5.47	1,610				
NE	4	191,498	5.81	4,552				
NH	3	79,585	9.46	2,095				
NJ	21	85,189	7.28	2,064				
NM	6	148,864	5.51	3,542				
NV	6	238,201	3.98	3,022				
NY	16	603,752	13.06	9,630				
OH	28	116,898	5.08	4,718				
OK	9	164,785	5.48	6,607				
OR	12	128,768	12.21	8,752				
PA	13	197,931	8.56	7,379				
RI	6	83,412	6.52	2,815				
SC	8	77,894	12.65	9,598				
SD	2	110,922	8.61	3,728				
TN	13	128,109	9.25	8,309				
TX	70	193,298	11.36	10,704				
UT	16	79,198	6.35	3,100				
VA	16	133,671	9.00	5,457				
VT	1	42,417	3.31	297				
WA	24	108,259	8.26	8,558				
WI	15	113,300	7.59	3,603				
WV	2	50,269	27.25	13,035				
WY	2	57,391	5.58	2,152				
Total	861	133,607	8.59	5,283	397	412	295	

Table 2: Dictionary and illustration of our methodology.
The table reports the dictionary of the words used to create climate disclosure and adaptation measures. Panel A reports climate exposure and adaptation dictionaries. For the two dictionaries, 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, and (iii) climate change summary for policymakers issued by the Intergovernmental Panel on Climate Change ("IPCC"). We then augment the dictionaries by manually reading disclosures from five sample cities over time (Fort Lauderdale, Miami, Miami Beach, Orlando, and Tampa). This process allows us to capture words that cities use to describe climate hazards or adaptation actions but may not be commonly used in CDP, C40, and IPCC guidance and reports. Panel B provides examples of the sentences with our two textual measures. The keywords used to identify the passages are italicized. Panel C presents our measures in the context of the financial disclosures and their typical paragraphs, using the example of the documents disclosed by Miami Beach. *Type* is the type of textual measure, with control *Type* exemplifying the paragraph that does not contain any of our textual measures. *Document Sentences* is the total number of sentences in the document. *Scaled Measure* is the number of sentences of a given *Type* in the presented paragraph, scaled by *Document Sentences*. *Paragraph Sentences* is the total number of sentences in the presented paragraph. *Paragraph Measure* is the number of sentences of a given *Type* in the presented paragraph.

Panel A: Dictionary.

Climate Exposure	Adaptation		
acid rain	beach nourishment	improve road drainage	stormwater inlet replacement
cold wave	bioswale	inlets	stormwater inspection
cyclone	breakwater	levee	stormwater maintenance
electrical storm	buyout program	living shoreline	stormwater management
emperor tide	catch basin repair	National Flood Insurance Program	stormwater master planning
extreme precipitation	culverts	pervious pavement	stormwater operation
extreme rain	detention storage systems	project stormwater	stormwater pond
flood	dike	project wastewat	stormwater project
fog	drain pipe	pump system	stormwater pump
heat wave	drainage channel	rain garden	stormwater pump station
heavy rain	drainage evaluation	rainwater capture	stormwater quality improvement
high tide	drainage facilities	raising streets	stormwater retention
hurricane	drainage improvement	recharge wells	stormwater retrofit
inundation	drainage infrastructure	retention basin	stormwater services
king tide	drainage line rehabilitation	retention pond	stormwater system
lightning	drainage mitigation	retention storage systems	stormwater vault
ocean acidification	drainage project	sand replenishment	street drainage
rain event	drainage rehabilition	sea level rise mitigation	surface water maintenance
rain fall	drainage replacement	sea level rise modelling	swale restoration
rain storm	drainage system	sea wall	tidal control valve
rainfall	drainage well	seawall	tidal valves
rainstorm	drainpipe	shoreline conservation	wastewat improv
rise tide	earthen berm	shoreline protection	wastewat project
rising sea levels	elevated roads	soil retention	water channel
rising temperature	erosion control	spillway	wet detention basin
salt water intrusion	exfiltration system	storm drain	wet pond
saltwater intrusion	flood control	storm hardening	wind mitigation
sea level rise	flood management	storm water infrastructure	wind resistance
severe wind	flood mapping	storm water management	wind retrofit
SLR	flood mitigation	storm water project	
storm catastrophy	flood prevention	StormReady	
storm damag	flood protection	stormwater administration	
storm event	flood relief	stormwater capture	
storm surge	flood restoration	stormwater catch basin	
storm water runoff	flood wall	stormwater collection	
stormwater runoff	floodwall	stormwater compliance	
subsidence	hurricane hardening	stormwater construction	
thunderstorm	hurricane preparedness	stormwater conveyance retrofit	
tidal event	hurricane protection	stormwater drain	
tornado	improve stormwater	stormwater equipment	
tropical storm	improve wastewat	stormwater evaluation	
typhoon	improve drainage	stormwater improvement	

Table 2: Dictionary and illustration of our methodology. Continued.

Panel B: Examples of the paragraphs that contain climate exposure and adaptation.

Textual Measure	Example Sentence	Source
Climate Exposure	"The State is naturally susceptible to the effects of extreme weather events and natural disasters including *floods*, droughts, and *hurricanes*, which could result in negative economic impacts on coastal communities such as the City. Such effects can be exacerbated by change in climate."	Tampa Bond 2020
Climate Exposure	"The City of Fort Lauderdale incurred expenditures between fiscal years 2017 and 2019 to recover from damages caused by *Hurricane* Irma, which occurred in September 2017."	Fort Lauderdale CAFR 2019
Adaptation	"The City has also updated the land development regulations to incorporate climate adaptation and resilience, such increasing *sea wall* height..."	Miami Beach CAFR 2019
Adaptation	"This project provides for small to medium sized *flooding relief* and failed pipe projects will be constructed under this city wide contract."	Tampa Budget 2018

Table 2: Dictionary and illustration of our methodology. Continued.

Panel C: Illustration of the magnitudes of climate exposure and adaptation measures with Miami Beach disclosures.

Document	Page	Paragraph	Type	Document Sentences	Scaled Measure	Paragraph Sentences	Paragraph Measure
2019 CAFR	4	Urban resilience is the capacity of individuals, communities, institutions, businesses and systems within a city to survive, adapt and grown, no matter what kinds chronic stresses and acute shocks they experience. One of the City's top resilience stresses is sea level rise, and the City has made a commitment to invest in aging infrastructure, adapt to sea level rise, and use the best available science to do so. This includes *elevating roads*, upgrading its gravity-based stormwater infrastructure with *tidal control valves*, pump stations, pipes, and other innovative structures to *improve drainage*. The City has also updated the land development regulations to incorporate climate adaptation and resilience, such increasing *sea wall* height, increasing base flood elevation, establishing freeboard above FEMA base flood elevation, requiring sea level rise and resiliency review criteria for Land Use Boards, introducing additional commercial height standards, and increasing set-backs and open space for single family homes. The natural resources, including the coral reef tract and the beach and our mature sand dune system protect the eastern side of our island from wave energy and storm surge events.	Adaptation	1725.00	11.59	5.00	2.00
2019 GO bonds	46	Projected changes in weather and tidal patterns place coastal areas like the City at risk of substantial wind or *flood* damage over time, affecting private development and public infrastructure, including roads, utilities, emergency services, schools, and parks. As a result, global climate change increases the potential of considerable financial loss to the City, including, without limitation, substantial losses in tax revenues. In addition, many residents, businesses and governmental operations could be severely disabled for significant periods of time or displaced, and the City could be required to mitigate these effects at a potentially material cost.	Climate Exposure	2469.00	4.05	3.00	1.00
2019 CAFR	2	The annual budget serves as the foundation for the City's financial planning and control. Prior to the first public hearing required by state law, the City Commission is presented with a proposed budget. The proposed budget includes anticipated expenditures and the means for funding them. After Commission review and two public hearings, the budget is adopted. The budget is approved by fund and department. Management may transfer amounts between line items within a department as long as the transfer does not result in an increase in the department's budget. Increases to funds or a department budgets and transfers between departments require Commission approval. Annual budgets are adopted on a basis consistent with GAAP for all governmental funds except the capital projects fund, which adopts project-length budgets. Budget-to-actual comparisons are provided in the required supplementary information section of this report for the general fund, the resort tax special revenue fund, and the Miami Beach Redevelopment Agency special revenue fund. Funds and grants that have multi-year project budgets are not presented in the statements.	Control	1725.00	0.00	10.00	0.00

Table 3: Summary statistics.
This table presents summary statistics on the associations between our textual climate exposure and adaptation measures and the city-specific characteristics. *All Documents Adaptation, Budget Adaptation, CAFR Adaptation, Bonds Adaptation* is the number of adaptation sentences scaled by the total number of sentences in all documents, budget, CAFR, and bond prospectuses, respectively, and multiplied by 10,000. *All Documents Exposure, Budget Exposure, CAFR Exposure, Bonds Exposure* is the number of climate exposure sentences scaled by the total number of sentences in all documents, budget, CAFR, and bond prospectuses, respectively, and multiplied by 10,000. *Total Sentences* is the total number of sentences per document. *Local Officials Should Do More* is a percentage of the respondents to the Yale Climate Opinion survey who believe that local officials can do more to address global warming. *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*.

Panel A: Descriptive statistics.

Variable	N	Mean	SD	p25	p50	p75
All Documents Adaptation	419	91.82	65.51	48.20	75.32	114.84
All Documents Exposure	419	45.91	40.59	20.11	33.13	57.54
Budget Adaptation	397	144.37	112.18	81.79	114.75	186.14
Budget Exposure	397	68.75	68.39	28.59	51.52	84.43
CAFR Adaptation	412	54.83	41.00	23.46	46.56	76.38
CAFR Exposure	412	31.35	38.73	8.31	21.04	40.70
Bonds Adaptation	154	15.48	32.53	3.08	8.00	15.00
Bonds Exposure	154	18.33	23.50	4.57	10.54	24.31
Total Sentences	419	4873.26	3052.31	2967.50	4290.00	6205.33
Local Officials Should Do More	419	57.93	4.50	53.93	58.99	60.34
Capital Budget Outlook	415	4.05	2.04	1.00	5.00	5.00
Population	419	115285.56	120960.59	57669.00	77216.00	113464.00
Total Debt per Capita	365	937.02	897.67	296.76	606.41	1311.45

Panel B: Descriptive statistics - party affiliation.

N	Democrat	Republican	Other
419	201	137	81

Table 3: Summary statistics. Continued.

Panel C: Univariate correlations

	Budget Adapt.	Budget Exp.	CAFR Adapt.	CAFR Exp.	Bonds Adapt.	Bonds Exp.	Local Off.	CB Outlook	Population	Debt p.c.
Budget Adaptation	1.00									
Budget Exposure	0.59	1.00								
CAFR Adaptation	0.45	0.15	1.00							
CAFR Exposure	0.19	0.24	0.25	1.00						
Bonds Adaptation	0.23	0.15	0.07	0.06	1.00					
Bonds Exposure	0.13	0.19	-0.10	0.26	0.50	1.00				
Local Officials Should Do More	-0.20	-0.06	-0.17	0.00	0.00	0.08	1.00			
Capital Budget Outlook	-0.01	-0.12	0.03	-0.00	0.02	0.04	-0.24	1.00		
Population	-0.11	-0.13	-0.08	-0.07	-0.00	0.03	0.07	-0.02	1.00	
Total Debt per Capita	-0.10	-0.06	-0.03	-0.08	-0.02	0.14	0.07	-0.06	0.58	1.00

Table 4: Validation of textual measures.
This table presents validation regressions of our climate disclosure and adaptation measures. Panel A presents difference-in-difference regressions relative to extreme weather events. Dependent variables are climate exposure and adaptation sentences, scaled by the total number of sentences in a document. In columns (1) and (2), we use the data on cities in the top and the bottom quartiles of the percentage properties, with *High Flood Risk* cities having top-quartile percentage properties at risk. In columns (3) and (4), we use all data in our sample, with *High Flood Risk* cities having above-median percentage properties at risk. *Post* is an indicator variable equal to one after an extreme weather event (for Floridian pilot study, this event is Hurricane Matthew of 2016). *Log(Population)* is a natural logarithm of population. We also include city-by-document type fixed effects. Standard errors are clustered at the city level. Panel B presents the association between our measures computed using the budgets and *Log(Fund Expense$_{t+1}$ + 1)*, total expenses from the city funds that are related to capital projects and emergency preparedness. In columns (1) and (2), the dependent variables are climate exposure and adaptation sentences calculated from all the available documents, scaled by the total number of sentences in these documents. In columns (3) and (4), the dependent variables are climate exposure and adaptation sentences calculated from the budget, scaled by the total number of budget sentences. 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 B drops because Muni Atlas only has fund-level data for 2017-2019.

Panel A: Validation: differences-in-differences with extreme weather events.

	Dependent variable:			
	Exposure	Adaptation	Exposure	Adaptation
	Top vs. Bottom Quartile		Top vs. Bottom Half	
	(1)	(2)	(3)	(4)
High Flood Risk × Post	31.59***	35.06**	24.95***	14.91
	(2.84)	(2.08)	(2.81)	(1.34)
Log(Population)	164.20	12.86	76.35	22.68
	(0.45)	(0.04)	(0.38)	(0.11)
City × Doc. Type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered s.e.	City	City	City	City
Observations	481	481	963	963
Adjusted R^2	0.59	0.66	0.55	0.63

Panel B: Validation: climate exposure and adaptation and fund expenses.

	Dependent variable:			
	Exposure	Adaptation	Exposure	Adaptation
	All documents		Budget	
	(1)	(2)	(3)	(4)
Log(Fund Expense$_{t+1}$ + 1)	0.92	1.81*	0.20	2.36
	(1.58)	(1.91)	(0.20)	(1.17)
Log(Population)	−216.15	−118.50	331.27	−301.82
	(−0.98)	(−0.25)	(0.92)	(−0.55)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered s.e.	City	City	City	City
Observations	71	71	71	71
Adjusted R^2	0.64	0.84	0.59	0.91

Table 5: Climate exposure and adaptation and city-specific characteristics.
This table presents the associations between our textual climate exposure and adaptation measures and the city-specific characteristics. In columns (1) and (2), the dependent variables are climate exposure and adaptation sentences calculated from all the available documents, scaled by the total number of sentences in these documents. In columns (3) and (4), the dependent variables are climate exposure and adaptation sentences calculated from the budget, scaled by the total number of budget sentences. *Local Officials Should Do More above median* is an indicator variable equal to one if a percentage of the respondents to the Yale Climate Opinion survey who believe that local officials can do more to address global warming is above sample median. *Republican* is an indicator variable equal to one if the city has a Republican mayor. *Capital Budget Outlook above median* is an indicator variable equal to one if the number of years in the capital budget, as reported is above median. *Population* is the total population of the city. *Total Debt per Capita above median* is an indicator that the total debt outstanding, scaled by *Population* is above median. *High Flood Risk* is an indicator variable equal to one if the city has above-median percentage properties at risk. We also include 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. Number of observations drops because Muni Atlas does not cover every city-year for our collected sample.

	Dependent variable:			
	Budget: Exposure	Budget: Adaptation	All docs: Exposure	All docs: Adaptation
	(1)	(2)	(3)	(4)
Republican	-30.74^{**}	-79.82^{***}	-13.51^{**}	-39.71^{***}
	(-2.55)	(-3.79)	(-1.99)	(-3.41)
Local Officials Should Do More above median	22.05	75.58^{***}	7.78	37.49^{***}
	(1.46)	(3.27)	(1.04)	(2.82)
Total Debt per Capita above median	-6.30	-30.41^{*}	-3.40	-10.47
	(-0.67)	(-1.69)	(-0.54)	(-0.96)
Capital Budget Outlook above median	-3.09	-21.00	0.27	1.41
	(-0.24)	(-0.78)	(0.03)	(0.09)
High Flood Risk	8.46	31.28	5.17	22.87^{*}
	(0.60)	(1.45)	(0.67)	(1.70)
Log(Population)	-11.32	-17.94	-10.70^{**}	-14.18
	(-1.37)	(-1.11)	(-1.99)	(-1.59)
Year FE	Yes	Yes	Yes	Yes
Clustered s.e.	City	City	City	City
Observations	347	347	365	365
Adjusted R^2	0.07	0.17	0.12	0.16

Table 6: Primary market tests: replication of Painter (2020).
This table presents a replication of the results of the Painter (2020) regressions of equation (1) on our data. In columns (1) - (2), the dependent variable is the offering spread, defined as the difference between offering yield and the maturity-matched yield from the treasury curve. In columns (3) - (4), the dependent variable is the offering spread. Painter (2020) also uses total annualized issuance cost, defined as a sum of offering yield and the gross spread (difference between the price underwriters paid for the issue and what price they sold the issue to the market). We do not use total annualized issuance cost because the gross spread data is missing for all observations in our sample. *Adaptation* is number of adaptation sentences in all documents, scaled by the total number of sentences. *Exposure* is number of climate exposure sentences in all documents, scaled by the total number of sentences. *Flood Risk* is the percentage of properties at risk in a city. Following Painter (2020), 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 and competitively issued. We do not control for whether the bond is federally tax-exempt, state tax-exempt, or subject to AMT because our data lacks variation in these variables. We also include state-year fixed effects. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

	Dependent variable:			
	Offering Spread			Offering Yield
	(1)	(2)	(3)	(4)
Adaptation		−0.0000		−0.0002
		(−0.04)		(−0.19)
Exposure		0.01**		0.004*
		(2.04)		(1.67)
Flood Risk	−0.05**	−0.07***	−0.02	−0.03
	(−2.11)	(−2.68)	(−0.65)	(−1.25)
Ln(Size)	5.71***	5.62***	4.95**	4.88**
	(2.65)	(2.68)	(2.37)	(2.36)
Ln(Maturity)	0.41***	0.37***	0.53**	0.51**
	(3.42)	(3.14)	(2.28)	(2.21)
Rating	0.10***	0.09***	0.10***	0.09***
	(6.85)	(6.41)	(4.63)	(4.39)
Callable	0.53***	0.54***	1.31***	1.32***
	(19.12)	(20.40)	(31.01)	(30.76)
Insurance	0.09	0.11	0.12	0.14
	(0.80)	(1.00)	(1.31)	(1.48)
Sinkable	0.33***	0.32***	0.57***	0.56***
	(6.23)	(6.38)	(7.40)	(7.65)
GO	−0.01	−0.03	0.12***	0.11***
	(−0.22)	(−0.42)	(3.00)	(2.70)
Pre-Funded	0.17**	0.18**	0.21*	0.22*
	(1.99)	(2.10)	(1.91)	(1.92)
Competitive	−0.12*	−0.12**	−0.22***	−0.22***
	(−1.96)	(−2.09)	(−3.29)	(−3.31)
Ln(CUSIPS/Issue)	−6.69***	−6.57***	−6.03**	−5.94**
	(−2.77)	(−2.81)	(−2.50)	(−2.50)
Ln(Underwriter Deals)	0.01	0.004	−0.02	−0.02
	(0.34)	(0.19)	(−0.56)	(−0.66)
State-Year FE	Yes	Yes	Yes	Yes
Observations	1,767	1,767	1,782	1,782
Adjusted R^2	0.64	0.65	0.66	0.66

Table 7: Primary tests: replication of Goldsmith-Pinkham et al. (2021)
This table presents a replication of the results of the Goldsmith-Pinkham et al. (2021) regressions of equation (1) on our data. *Adaptation* is number of adaptation sentences in all documents, scaled by the total number of sentences. *Exposure* is number of climate exposure sentences in all documents, scaled by the total number of sentences. *Flood Risk* is the percentage of properties at risk in a city. Observations are at the bond-year-month level. The dependent variable is the volume-weighted average credit secondary spread of a municipal bond. Spread is defined as the difference between yield-to-maturity and the maturity-matched yield from the treasury curve. Following Goldsmith-Pinkham et al. (2021), we include controls for the logarithm of the bond's time to maturity, callability and insured status interacted with the year; and 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. t-statistics are reported in parentheses, with standard errors clustered by city and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

	Dependent variable:	
	Secondary Spread	
	(1)	(2)
Adaptation		-0.002^{***}
		(-2.71)
Exposure		0.01^{**}
		(2.40)
Flood Risk	0.01	-0.01
	(0.22)	(-0.15)
Log(Time to Maturity)	0.07	0.08
	(0.62)	(0.68)
City Average Income	-0.0000^{**}	-0.0000^{***}
	(-2.43)	(-3.38)
GO Bond	-0.23^{*}	-0.27^{**}
	(-1.83)	(-2.41)
Time from Issuance	-0.13	-0.13^{*}
	(-1.65)	(-1.68)
Trading Volume/Amount Outstanding	-0.002	-0.003
	(-0.04)	(-0.05)
SD(Monthly Transaction Prices)	0.24^{**}	0.23^{**}
	(2.55)	(2.51)
Insured $\times$ Year	-0.0001	-0.0001
	(-0.40)	(-0.63)
Callable $\times$ Year	-0.0002^{*}	-0.0002^{*}
	(-1.89)	(-1.96)
Trade-Month FE	Yes	Yes
Observations	25,625	25,625
Adjusted R^2	0.09	0.10

Online Appendix

Appendix A.

Figure A1: 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.

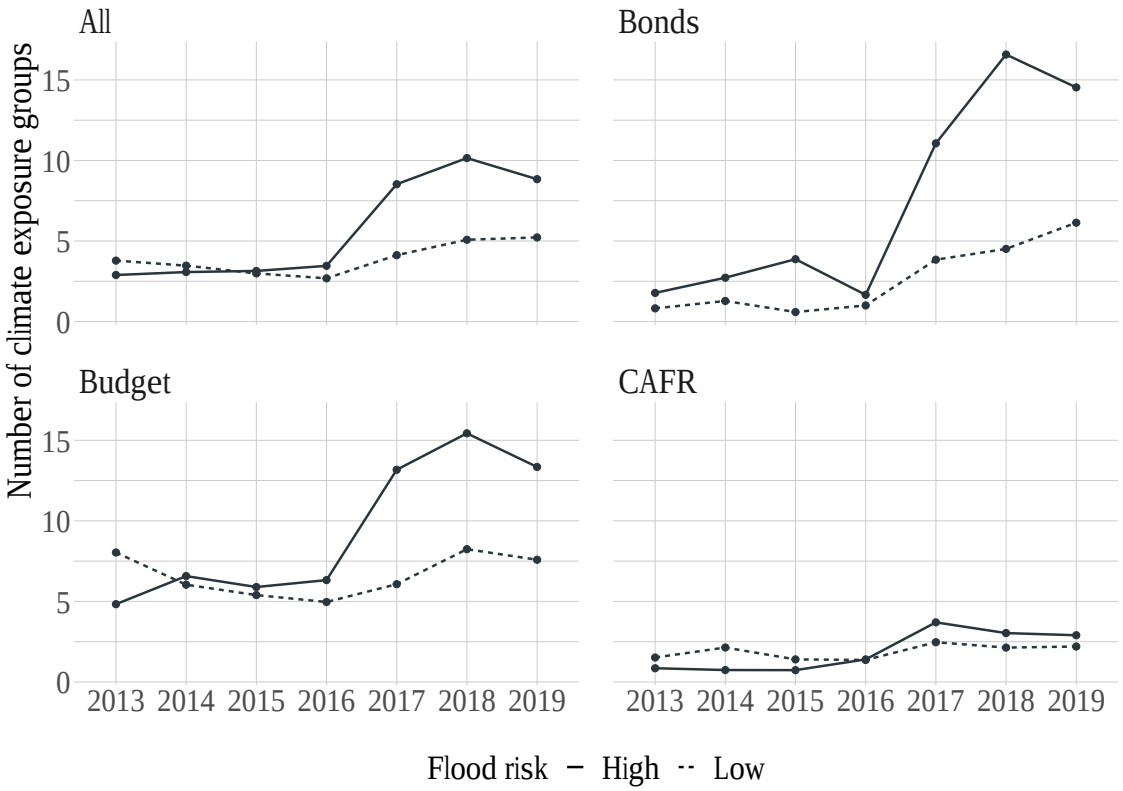
AREAS UNDER CONSIDERATION:

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

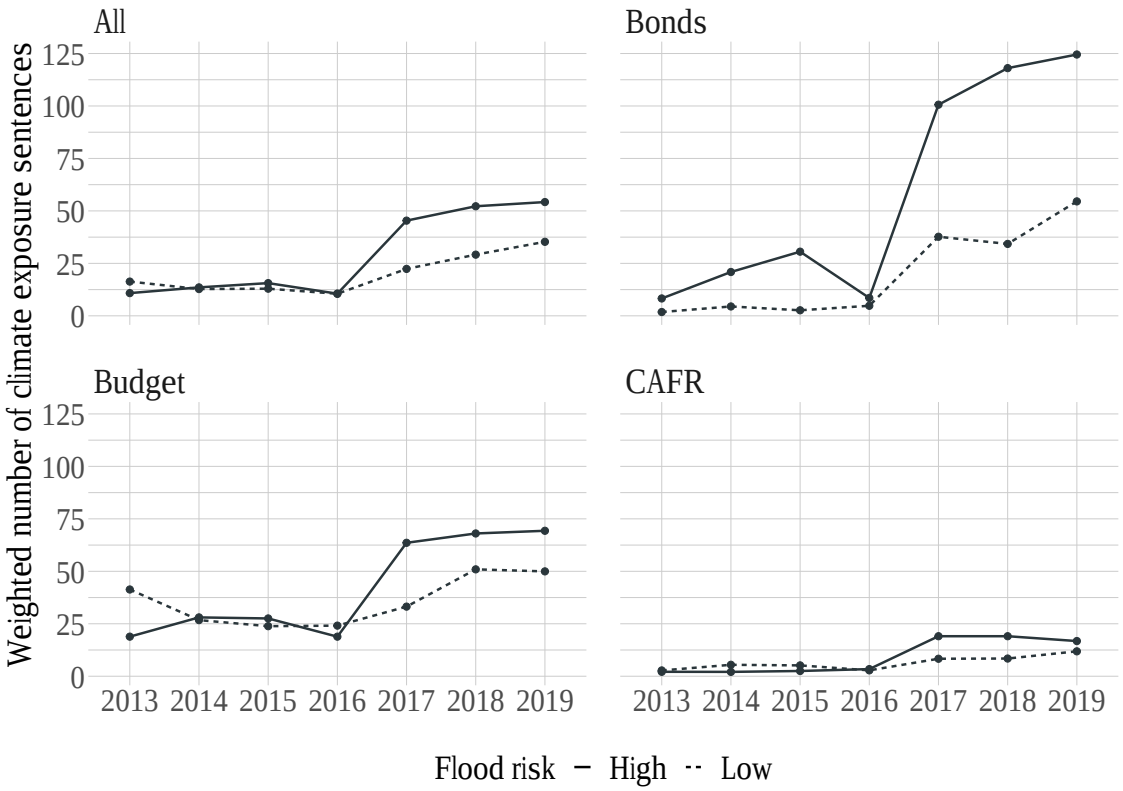
Appendix B.

Figure B1: Number of groups.
This figure plots the number of groups containing exposure keywords in a document. A group is defined as three or more keywords within five sentences of each other.



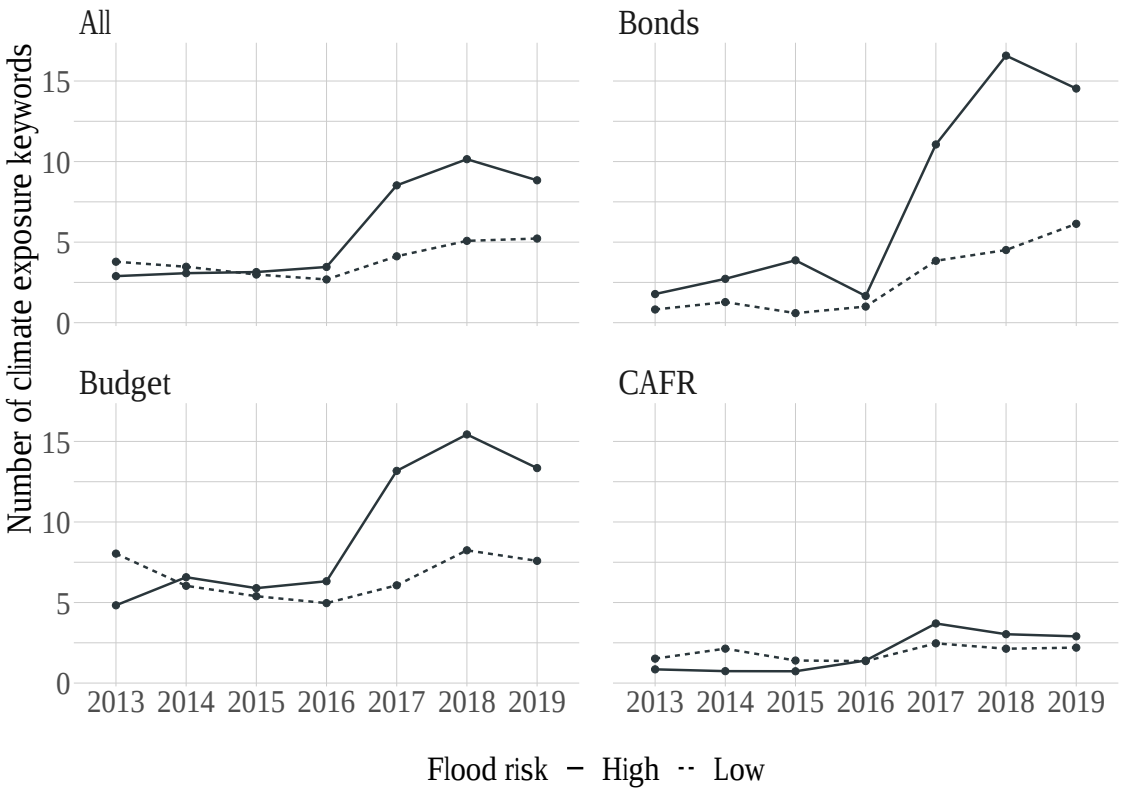
Appendix C.

Figure C1: Weighted total number of sentences.
This figure plots the weighted total number of sentences with exposure keywords. Sentences are weighted by their position in the report, with sentences that appear earlier in the document having higher weights.



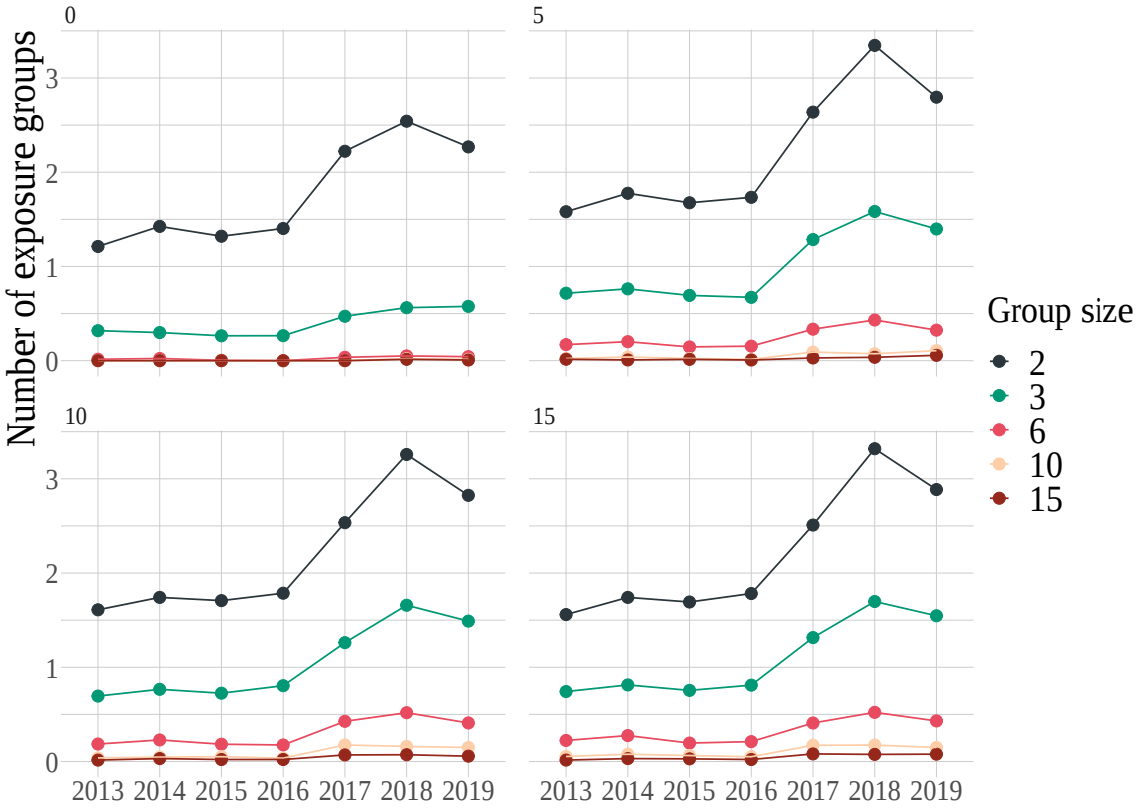
Appendix D.

Figure D1: Number of keywords.
This figure shows the measures using the count of exposure keywords in the dictionary instead of count sentences.



Appendix E.

Figure E1: 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 F.

Figure F1: Hazard types.
This figure plots the different types of climate hazards disclosed in the Florida sample. Each hazard is calculated using all documents over the sample period, 2013-2019.

