Measuring Cities' Climate Risk Exposure and Preparedness

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Early draft – comments are welcome.

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 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 find that climate-change adaptation is lower in cities that face capital constraints and for cities with Republican mayors. The second effect is muted in cities where residents report a higher concern for climate change. Additionally, municipal bond market lowers the climate risk premium when city-level adaptation is high.

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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).

However, the existing climate risk measures are limited 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 standalone preparedness plans, they are required to regularly disclose

[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.

such information as part of their financial disclosures. By taking a textual analysis approach, we take advantage of the unique richness of municipal financial disclosures. Cities' annual reports and bond prospectuses disclose material climate risks and discuss 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 employ a dictionary-based approach for textual analysis (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 present in the guides and reports. For example, cities talk about "king tide," "swale restoration," and "tidal valve," terms that are not present in other sources. Our current dictionaries for exposure and adaptation contain 44 and 121 keywords, respectively.

We hand collected financial reports and applied the textual analysis methodology for 356 cities in 41 states and the District of Columbia. This sample represents cities with above 40,000 population in coastal states, and above 150,000 population in non-coastal states.[3] On average, in each financial report, a city discloses 5 sentences about climate exposure and 7 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 test whether *exposure* increases after major hurricanes. Using the staggered timings of hurricanes in different states, we find that *exposure* increases significantly for cities with a higher flood risk after a hurricane that caused at least $1 billion damage to the state. To validate our adaptation measure, 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 are particularly interested in shedding light on constraints that limit a city's preparedness for climate risks. First, we examine the association between 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

[3] We focus on coastal states in the current sample to maximize power. We intend to expand the sample further based on analysis on this initial set of cities.

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. Comparing cities within the same county, and hence face similar flood risk, we find that cities with Republican mayors are associated with a lower *adaptation*. This relationship, however, is mitigated if there is high concern for climate change in the county.

Second, we examine the city's capital constraints. Because adaptation is costly, capital constraints can explain why some cities are not investing in adaptation, despite city management and constituents recognizing the danger of flood risks. We find that *adaptation* is significantly higher for cities with more unrestricted funds relative to expenses and with a lower amount of outstanding debt. This result is consistent with capital constraint being a potential reason for the lack of flood preparedness.

Finally, we examine the length of the capital budget outlook to identify whether cities with a more extended planning horizon can better plan for climate events, which are long-term risk. We find suggestive evidence that cities with longer planning horizons have higher climate preparedness, but only in counties with high concern for climate change.

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 exposure. 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. We find that climate risk is positively correlated with bond spread, whereas our measure for climate adaptation mitigates this relation and is negatively correlated with bond spread.

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.

Second, our paper provides evidence on the factors that explain why some cities are less prepared for climate risks. We examine how political beliefs, the capital budget outlook, and capital 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 capital constraint is a key predictor of adaptation, future research can investigate the causal importance of capital constraints, and policymakers can consider grants and 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, other 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.[4] By measuring adaptation directly, we can empirically examine which city-specific characteristics are

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

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 after 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.[5]

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 officials 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

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

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 8.04%.

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 Sample

We collect municipal financial documents from 2013-2019 for 356 cities in 41 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 focus on states along the East and Gulf coast because these are states most prone to flood risk. For the remaining states, we collect data for cities with population above 150,000 people. 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. **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 285,119, where 8.04% (or 9,487) of properties are at risk of flooding.

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).

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 cities 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 rising sea levels. 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. Additionally, the disclosure of climate risk exposure can also be affected by beliefs, where cities with a strong belief in climate change may disclose more information about climate risks.

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. This list includes 9 cities in Massachusetts, 5 cities in Florida, and Washington DC.[6] This process allows us to capture words that local governments use to describe climate hazards or adaptation actions, but that may not be commonly used in guidance and reports issued by other organizations. Some examples include "king tide," "rainstorm," and "stormwater improvement."

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

[6] Massachusetts: Boston, New Bedford, Quincy, Cambridge, Newton, Somerville, Salem, Beverly, Revere. Florida: Fort Lauderdale, Miami, Miami Beach, Orlando, and Tampa

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 keywords with high occurrences. Specifically, we read disclosures where there are more than 100 references to a given keyword in a single document, as well as re-examine keywords with more than 0.5 occurrence in an average document. 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. For unstemmed keywords, we retain multiple versions of the keywords, such as "dike" and "dikes". 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 Tika 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 Tika package. For these samples, we use Optical Character Recognition Python-tesseract 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 raw measures capture the number of sentences that contain keywords from the corresponding dictionary. 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. For better interpretation in regression analysis, we scale our textual measures by the total number of sentences in a document, winsorize at the 99th percentile to prevent impact from outliers, and normalize the measure for better comparability. 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 measures 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, the scaled measure multiplied by 10,000 for interpretation purpose is 11.59 (2/1,725*10,000). Similarly, in the second paragraph, the first sentence contains exposure keywords, which translate to a scaled exposure measure of 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.

3.3 Descriptive statistics

Table 3 Panel A shows the distribution of our climate textual measures. The 2486 city-years have an average of 4.55 *exposure* sentences and 7.47 *adaptation* sentences. Budgets have the highest measures of 7.92 for *exposure* and 14.03 for *adaptation*. This observation is consistent with the idea that cities discuss adaptation actions in capital improvement plans in the budgets. This is followed by bonds, with a measure of 3.22 for *exposure* and 3.90 for *adaptation*. CAFR have the lowest textual measure of 2.14 for *exposure* and 3.44 for *adaptation*.

Figure 1 plots the climate exposure and adaptation measures over the years, and split by cities with below- and above-median flood risk within each state. For *exposure*, there is a gradual increase in frequency for cities with above-median flood risk after 2016 across all three document types. For *adaptation*, most of the variation is driven by budgets, where over time, there is a gradual increase in frequency for cities with above-median flood risk.

Table 3 Panel C shows that the adaptation and exposure measures are positively correlated with flood risk. **Figure 2** plots the map of US with the average flood risk, *exposure*, and *adaptation* by each state. Visually, there is many overlaps between the map for flood risk and *exposure*, where both are larger along coastal states, especially along the gulf coast. Relatively, *adaptation* exhibit more variation, which we attempt to understand more via the determinants analysis in Section 4.

3.4 Measurement validation

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

First, we validate the timing of our climate exposure measures by exploiting the staggered timing of hurricanes in different states. We expect climate exposure measure to be higher after the state is affected by hurricanes. To illustrate this validation using Florida as an example, we observe a jump in climate exposure measures for cities in Florida starting 2016, which is the year Hurricane Matthew hit and caused 6 deaths in October of 2016 (ABC News, 2016). To identify hurricane events across the US, we use the NOAA National Centers for Environmental Information ("NCEI") U.S. Billion-Dollar Weather and Climate Disasters dataset (NCEI, 2021). This dataset identifies climate events with damage or costs of over $1 billion.

We run a difference-in-differences analysis to compare our textual measure for cities with low and with high flood risks within a state. Low flood risk cities serve as the control. We expect that after a hurricane, cities with a higher flood risk will have a higher textual measure than will those in the control group. Specifically, we test:

$$\textit{Textual Measure}_{it} = \beta_1 \textit{High Flood Risk}_{it} \times \textit{Post}_{it} + \beta_2 \textit{High Flood Risk}_{it} + \beta_3 \textit{Population}_{it} + \beta_4 FE + \epsilon_{it} \quad (1)$$

where $TextualMeasure_{it}$ is the textual measure for city 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 within a state, depending on the specification. *Post*$_{it}$ is an indicator that equals 1 for observations after which the state experienced a hurricane identified in the NCEI dataset. We control for the size of the cities by including $Population_{it}$, which is the logarithm of annual population from Muni Atlas. We include state and year fixed effects to control for time-invariant differences in the textual measures for each state and each year. We cluster standard errors by state to address any potential correlations between different observations in a state, especially because the hurricanes data are at the state-level.

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, there is a 35 percent increase in *exposure* for cities above the median flood risk after hurricane events. 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.

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] Because of the limited number of cities with relevant fund expenses, and because the Muni Atlas fund-level data starts in 2017, the sample size drops significantly. Nonetheless, the coefficient on the fund expense is positive and statistically for *adaptation* in both budgets and all the documents. While we do not have a strong prediction for *exposure*, the coefficient on the fund expense is also positive and statistically significant in all documents, but not for budgets.

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

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. We manually examine the disclosure trends in five Florida cities: Fort Lauderdale, Miami, Miami Beach, Orlando, and Tampa. This initial reading is done 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, going forward, we will include two additional variants of the textual measures in order to quantify other dimensions of the disclosure. First, we plan to 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 for cities in Florida. 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 for cities in Florida.

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 for cities in Florida. The overall trends are similar to that if we plot adaptation and exposure sentences for the same sample. 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 a sample of Florida cities. 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:

$$\textit{Textual Measure}_{it} = \beta_1 \textit{Determinants}_{it} + \beta_2 \textit{Flood Risk}_{it} + \beta_3 \textit{Population}_{it} + \beta_4 FE + \epsilon_{it} \tag{2}$$

where *Textual Measure*$_{it}$ is the textual measure of climate risks for city i at time t. *Determinants*$_{it}$ are determinant variables, which we explain in subsequent subsections. We control for the city's flood risk and population size. *Flood Risk*$_{it}$ is the flood risk measure from the First Street Foundation. $Population_{it}$ is the logarithm of the city population from Atlas. We include county-year fixed effects to control for time-variant changes in each county.[8] Conceptually, county-year fixed effects allow us to compare the adaptation of cities within a county, where these cities should face similar flood risk. We cluster standard errors by state to address any potential correlations between different observations in a state.

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.,

[8]For cities that are located across multiple counties, we allocate it to the county with the largest population.

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 2,486 city-year observations, 1,028 have a Democratic mayor, 651 have a Republican mayor, and 807 have mayors that are neither Republican or Democratic, or are cities run under council-manager system, where the main decision-maker is non-partisan manager who is hired by city council. 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 in each state. Similarly to the results in **Figure 1**, we observe an increase in *exposure* and *adaptation*, but only for cities with a high flood risk. The figures do not demonstrate large differences between cities with Republican or Democratic mayor.

Table 5 shows the results from running regression (2), where one of the $Determinants$ variable is *Republican*, defined as an indicator for cities with a Republican mayor. We separately show results for *exposure* and *adaptation*, for all document types, budgets, and bonds. We examine the determinants of budgets' textual measures separately because budgets contain forward-looking information on where the city plans to allocate money in the future. We also run separate analyses for the bond prospectuses' textual measures because they contain information about the intended usage of raised funds.

When *adaptation* is the outcome variable, the coefficient on *Republican* is negative and statistically significant across all specifications. Using the specification in Column 2, this suggests that cities with Republican mayors have a lower *adaptation* of 29 percent.

We observe a similar negative correlation in climate exposure measures in cities with Republican mayors, but it is only statistically significant in all documents and in bonds. Using the specification in Column 1, this suggests that cities with Republican mayors have a lower *exposure* of 18 percent. This result is consistent with Republican mayors placing a lower emphasis on flood risks and investing less in adaptation.

As an additional analysis, in **Table 6** we examine if this result holds in cities where the local concern about climate change is high. We use the 2014 Yale Climate Opinion Survey data, which provides county-level beliefs about climate change in the US.[9] We use the county-level responses to the following prompt to capture people's concern about the impact of climate change: "How worried are you about global warming?" We take the percentage of the respondents who agree with this statement and create an indicator *Worried* for cities where this measure is above the median. In **Table 5** Columns 1 and 2, we interact *Republican* with *Worried*, and find that the coefficient on the interaction term is positive and statistically significant. This result suggests that while Republican mayors are on average less prepared for climate change, Republican mayors that govern in areas where citizens are concerned about climate change consequences both disclose more about *exposure*

[9] 2014 was the first year when Yale Climate Opinion Survey was conducted.

and invest more in *adaptation*.

4.2 Capital constraint

Our second determinant examines if capital 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 capital constraint to correlate with climate adaptation.

We measure capital constraints using two variables. The first is the ratio of unrestricted fund balance to net expenses (*Unrestricted fund balance*), where a higher ratio reflects a lower capital constraint because the city has a higher unrestricted funds relative to its expenses. The second is the outstanding debt per capita from Muni Atlas, where a higher debt reflects capital constraint in the sense that cities with a lower level of debt has less leverage, and hence may be able to borrow more to fund adaptation projects.

Figure 3 Panel B plots the textual measures in separate time series for cities above and below the median *Unrestricted fund balance*, and for cities above and below the median flood risk in the state. For *exposure*, cities with high flood risk increase over the years, but the increase is larger for cities with high *Unrestricted fund balance*. For *adaptation*, since 2013, cities with a high *Unrestricted fund balance* have higher *adaptation*. Over the years, there is gradual increase in *adaptation* with the exception of cities with low flood risk and high *Unrestricted fund balance*.

In the determinants regression in **Table 5**, across all specifications, consistent with capital constraint being a determinant of low climate preparedness, the coefficient on *UFB/Total Expense* is positive and the coefficient on *Log*(*Total Debt per Capita*) is negative. However, the results on *UFB/-Total Expense* are not statistically significant except for *exposure* in all documents. For *Log*(*Total Debt per Capita*), the effects are most significant for *adaptation* in all documents and in budgets. These results suggest that capital constraint may explain the lack of climate preparedness, consistent with the responses from the CDP survey.

In **Table 6**, when we interact the capital constraint variables with *Worried* in columns 3 to 6, none of the interaction terms are statistically significant. This result suggests that the lack of financial resources in explaining the lack of climate preparedness is not mitigated in counties with a higher concern for climate change.

4.3 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 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 has a capital budget outlook of four years, whereas the median is five years.

Figure 3 Panel C 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 in the state. 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 from the beginning since 2013, and gradually increases over time, but those with a low capital budget outlook remain flat.

Table 5 shows the regression results for the determinants analysis. The coefficient on *Capital Budget Outlook* is not statistically different from zero in all specifications. In **Table 6** columns 7 and 8, if we look at counties with high concern for climate change, the coefficient on the interaction of *Capital Budget Outlook* and *Worried* is positive for both *exposure* and *adaptation*, but only statistically significant for *exposure*. This provides suggestive evidence that planning horizon only correlate with better climate preparedness in counties that are concerned about climate change.

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.[10]

[10]See, for example, *Climate change blamed for devastating German floods*, Financial Times, July 16, 2021.

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. We begin with Painter (2020), that studies 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:

$$\text{Issuance Cost}_{it} = \beta_1 \text{Climate Risk}_{it} + \beta_2 X_{it} + \beta_3 FixedEffects + \epsilon_{it} \tag{3}$$

where Issuance Cost_{it} is the offering yield for bonds issued by municipality i at time t, 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. We normalize all three variables for better comparability of magnitudes. 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 for whether the bond is callable, insured, sinkable, pre-refunded, funded by general obligation, competitively issued, federally tax-exempt, state tax-exempt, or subject to AMT. Just like in Painter (2020), we include state-year fixed effects and cluster standard errors by county.

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 7 shows the results from our replication of Painter (2020). When we only include the flood risk measure in Columns 1, the coefficient on *Flood Risk* is positive but not statistically significant. When we include our textual measures in Columns 2, the coefficient on *Adaptation* is negative and 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.

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:

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

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. We normalize all three variables for better comparability of magnitudes. 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. Just like in Goldsmith-Pinkham et al. (2021), we include trade-month fixed effects and cluster standard errors by county and year-month.

Table 8 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 and statistically significant. In Column 2, when we include our textual measures, the coefficient on *Adaptation* is negative and statistically significant, which is consistent with adaptation mitigating this risk exposure (but to a smaller extent). The coefficient on *Exposure* is negative but not statistically significant, which is inconsistent with the market requiring a higher return for holding bonds with a higher climate risk exposure. One potential explanation is that the flood risk measure subsumes some of the variation of *Exposure*. The remaining variation in *Exposure* may reflect cities that provide more disclosure about climate exposures, and this higher transparency may be associated with a lower spread.

6 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.

We examine how party affiliation, capital constraints, and the budget planning horizon help explain a city's climate preparedness. Furthermore, we re-examine how the municipal bond market prices climate risks as well as cities' adaptation measures.

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. Going forward, there may be opportunity to apply this methodology to other climate-change-related risks.

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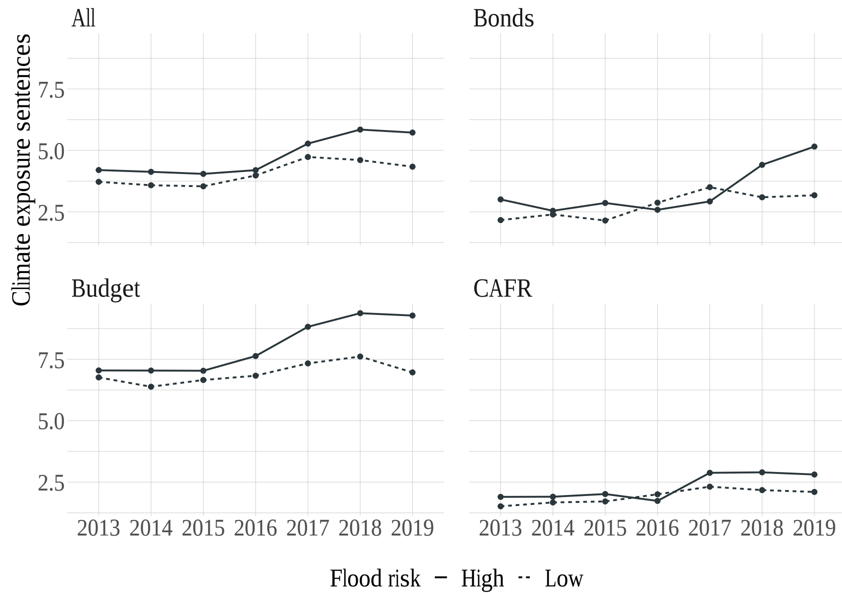
Figure 1: Climate disclosure and adaptation measures over time and by flood risk.
This figure presents climate disclosure and adaptation measures in all documents, budgets, CAFRs, and bond prospectuses over the sample period, 2013-2019. The solid line depicts the trends for high flood risk cities, and 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.

Panel A: Climate Exposure



Panel B: Adaptation

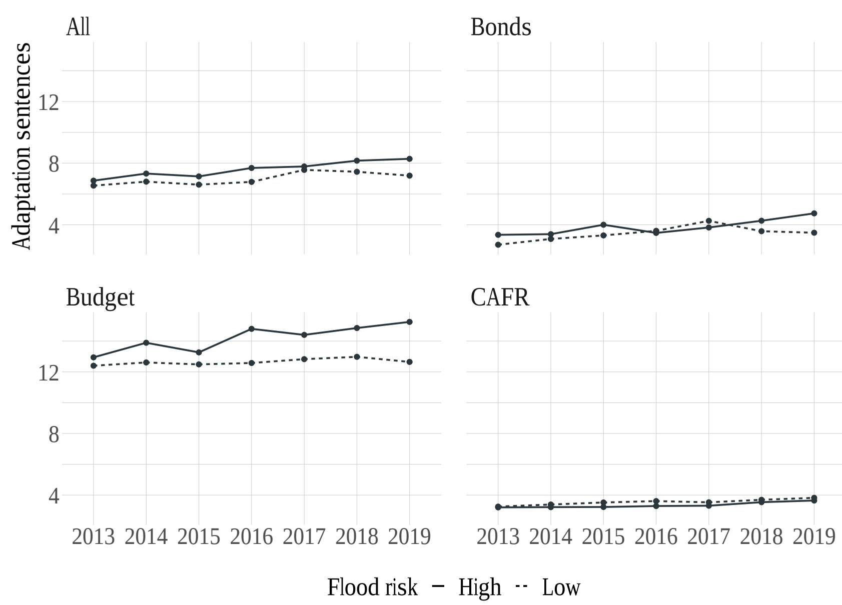
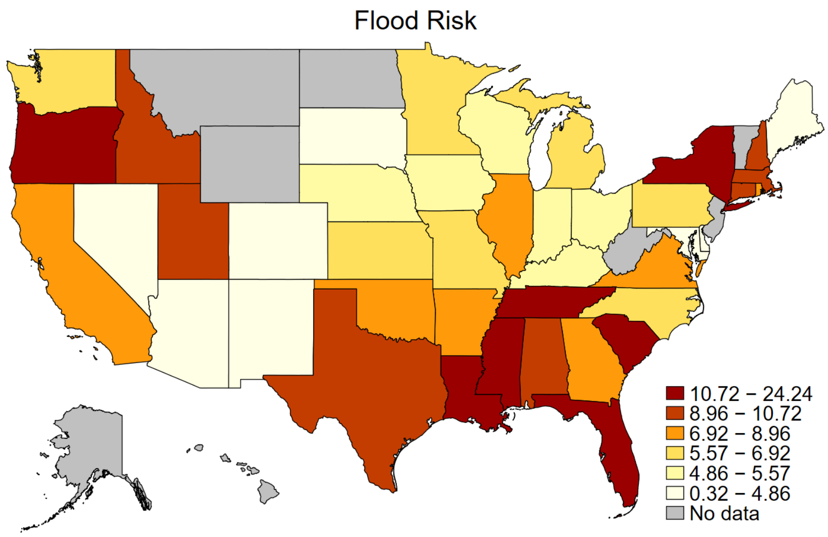
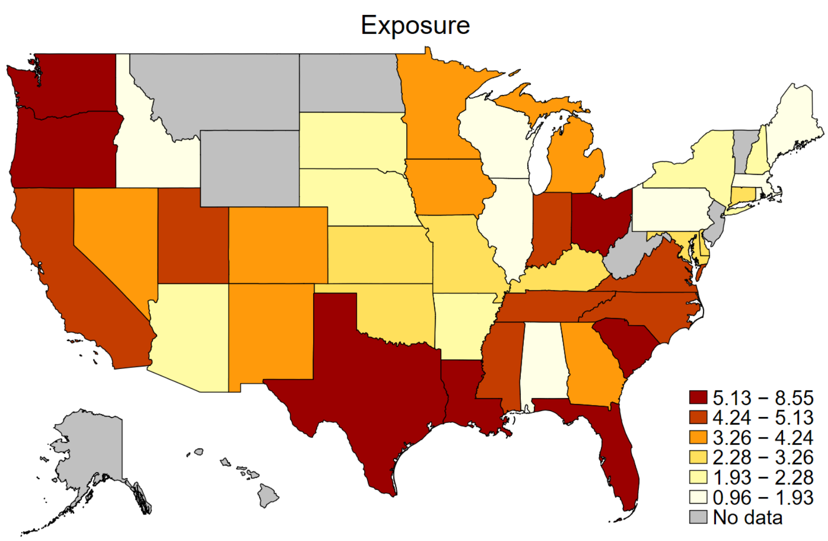


Figure 2: Flood risk, climate disclosure and adaptation measures by state.
This figure plots the climate disclosure and adaptation measures across states. Panel A plots the flood risk. Panel B plots the climate exposure sentences. Panel C plots the adaptation sentences. Both exposure and adaptation sentences averaged within-state over the sample period, 2013-2019.

Panel A: Flood risk



Panel B: Exposure



Panel C: Adaptation

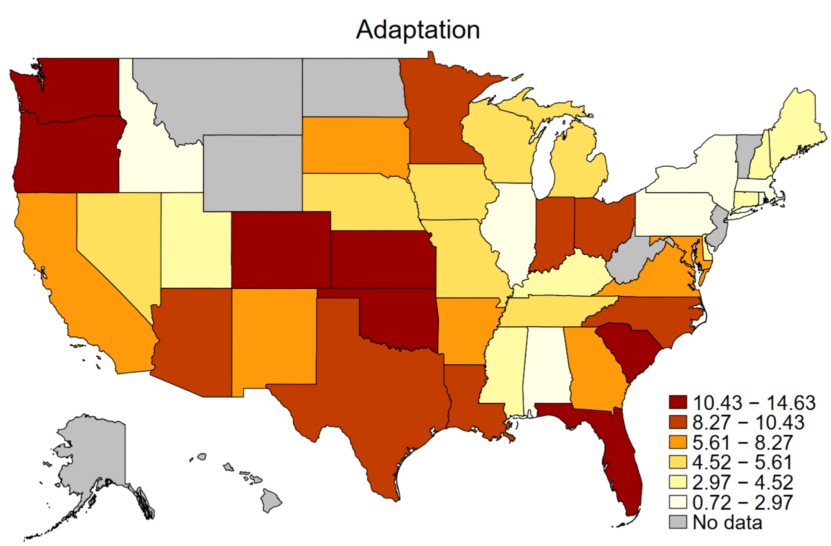
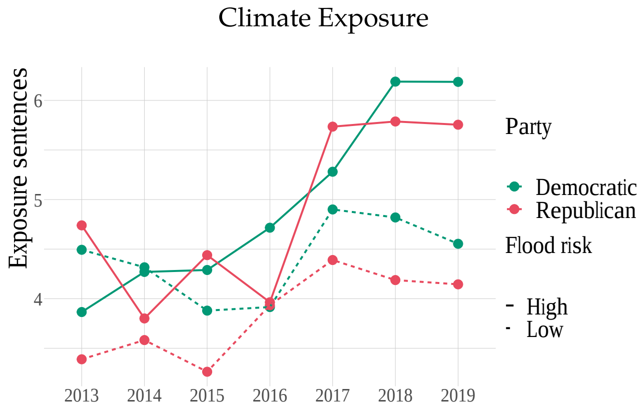
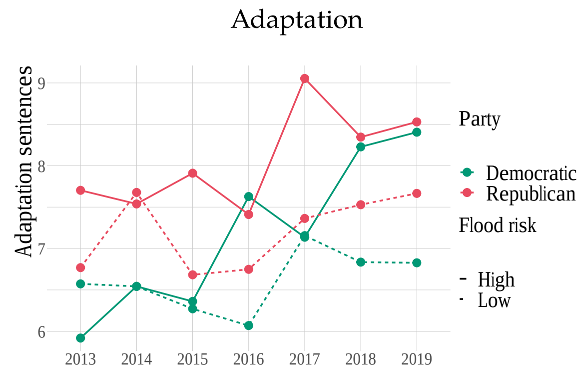


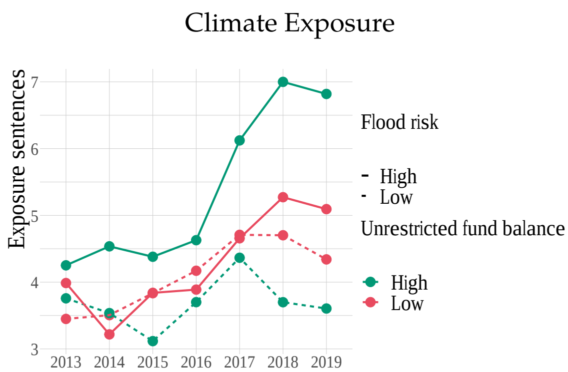
Figure 3: Climate exposure and adaptation over time and by flood risk.
This figure presents climate disclosure and adaptation measures in all documents over the sample period, 2013-2019. The solid line depicts the trends for high flood risk cities, and the dashed line shows the trends for low flood risk 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 unrestricted fund balance to net expense ratio. Panel C plots exposure and adaptation sentences by the length of capital budget outlook.

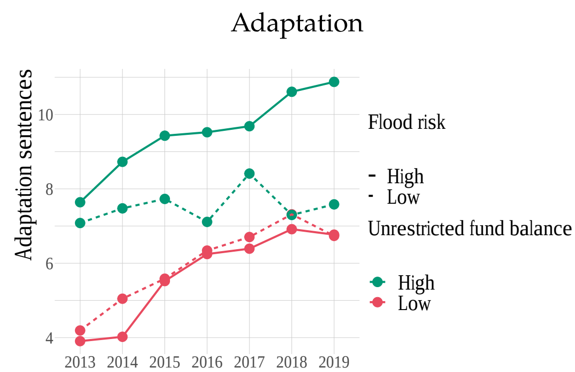
Panel A: Political affiliation



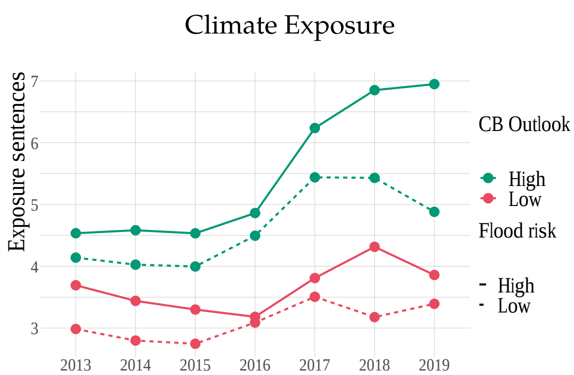


Panel B: Capital constraint





Panel C: Capital budget outlook



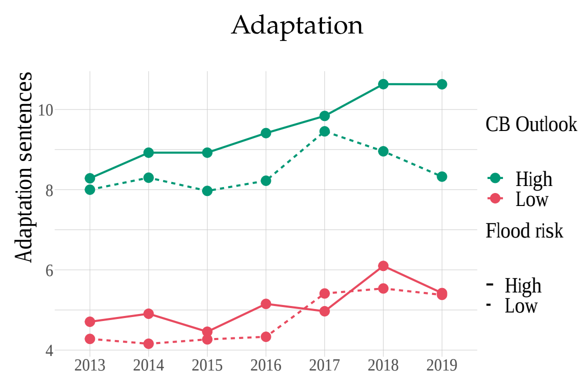


Table 1: Sample composition by state.
The sample comprises the cities with flood risk data from First Street Foundation and financial data from Muni Atlas. We focus on states along the East and Gulf coast because these are states most prone to flood risk. For these states, we collect data on all cities with 2010 U.S. Census population of over 40,000 people. For the remaining states, we collect data for cities with population above 150,000 people. This selection procedure yields 356 cities in 41 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.

State	N Cities	Population	Properties at risk, %	Properties at risk, total	N Budgets	N CAFRs	N Bond prospectuses
AL	9	124,145	10.11	11,654	62	63	57
AR	1	193,524	7.46	8,260	7	6	8
AZ	9	401,028	0.32	838	98	63	127
CA	33	422,150	7.89	10,321	239	231	322
CO	3	447,221	3.66	7,606	21	21	22
CT	13	87,426	10.48	2,538	111	91	125
DC	1	602,723	5.30	7,300	46	7	91
DE	1	70,851	4.28	1,494	7	7	4
FL	55	115,637	24.21	16,599	415	382	278
GA	5	163,574	7.90	8,630	35	35	28
IA	1	203,433	5.32	5,291	7	7	17
ID	1	205,671	9.51	14,778	8	7	5
IL	3	1,015,456	8.47	29,926	21	20	41
IN	1	253,691	5.02	6,855	39	7	6
KS	2	277,870	5.83	10,000	21	14	63
KY	1	295,803	5.57	6,713	7	7	17
LA	8	133,648	20.54	14,626	71	54	38
MA	41	73,866	10.79	2,128	315	330	659
MD	3	249,136	4.03	6,527	21	21	34
ME	1	66,194	4.86	1,511	7	7	8
MI	2	450,908	6.30	15,968	21	14	31
MN	1	382,578	5.97	8,310	7	7	38
MO	3	312,860	5.89	12,347	20	21	67
MS	4	84,070	11.04	5,661	17	26	104
NC	15	188,982	6.88	7,067	244	106	98
NE	2	333,668	4.99	7,338	11	14	28
NH	3	79,585	9.46	2,095	21	21	24
NM	1	545,852	1.41	3,319	7	7	13
NV	4	320,917	2.45	3,374	28	28	43
NY	13	726,520	12.87	10,977	356	75	427
OH	5	393,422	5.04	13,137	42	35	136
OK	2	485,952	7.20	21,558	19	11	53
OR	3	298,199	17.29	21,945	32	20	45
PA	7	314,172	6.87	10,332	55	47	93
RI	4	95,572	7.01	3,582	48	28	12
SC	6	89,872	14.81	11,717	37	40	56
SD	1	153,888	3.43	2,192	6	4	4
TN	3	331,146	14.20	22,404	24	21	19
TX	64	205,759	10.26	10,557	523	449	737
UT	1	186,440	10.37	10,612	7	7	31
VA	15	139,741	8.96	5,621	212	105	113
WA	3	322,949	5.98	15,551	21	21	26
WI	2	414,021	5.43	8,664	14	14	59
Total	356	285,119	8.04	9,487	3,330	2,501	4,207

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 fifteen sample cities over time (nine cities in Massachusetts, five cities in Florida, and Washington DC). 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 A: Dictionary.

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

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

Panel B: Examples of the paragraphs that contain climate exposure and adaptation.
Panel B provides examples of the sentences with our two textual measures. The keywords used to identify the passages are italicized.

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.
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, Florida. *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* (multiplied in this table by 10,000 for interpretability). *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 (multiplied by 10,000 for interpretability).

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 in all documents, budget, CAFR, and bond prospectuses. *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. *Total Sentences* is the total number of sentences per document. *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	2486	7.47	8.29	2.00	5.00	10.00
All Documents Exposure	2486	4.55	5.83	1.00	2.67	5.67
Budget Adaptation	2323	14.03	16.75	3.00	9.00	20.00
Budget Exposure	2323	7.92	10.65	2.00	4.00	10.00
CAFR Adaptation	2421	3.44	3.97	1.00	2.00	5.00
CAFR Exposure	2421	2.14	3.52	0.00	1.00	3.00
Bonds Adaptation	1666	3.90	9.76	0.50	2.00	5.00
Bonds Exposure	1666	3.22	7.49	0.00	1.00	3.00
Total Sentences	2486	5785.28	9133.87	2929.94	4570.00	6458.75
Capital Budget Outlook	2176	4.14	2.16	1.00	5.00	5.00
Population	2486	237753.90	551561.02	63125.25	112036.50	216562.75
Total Debt per Capita	2449	1775.43	1553.39	826.27	1400.46	2261.91

Panel B: Descriptive statistics - party affiliation.

N	Democrat	Republican	Other
2486	1028	651	807

Table 3: Summary statistics. Continued.

Panel C: Univariate correlations

	Budget Adapt.	Budget Exp.	CAFR Adapt.	CAFR Exp.	Bonds Adapt.	Bonds Exp.	Flood Risk	CB Outlook	Population	Debt p.c.
Budget Adaptation	1.00									
Budget Exposure	0.62	1.00								
CAFR Adaptation	0.37	0.29	1.00							
CAFR Exposure	0.19	0.32	0.33	1.00						
Bonds Adaptation	0.18	0.21	0.36	0.19	1.00					
Bonds Exposure	0.15	0.32	0.22	0.44	0.46	1.00				
Flood Risk	0.23	0.29	0.18	0.30	0.19	0.27	1.00			
Capital Budget Outlook	0.22	0.14	0.10	-0.02	0.04	0.04	-0.07	1.00		
Population	0.05	0.04	0.06	0.10	0.02	0.07	-0.09	0.02	1.00	
Total Debt per Capita	-0.08	-0.04	-0.12	-0.12	-0.03	-0.03	-0.12	0.09	0.22	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, winsorized at 1%, and standardized. 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, defined as NOAA-assessed billion dollar damage tropical cyclon (e.g., for Florida this event is Hurricane Matthew of 2016). *Log(Population)* is a natural logarithm of population. We also include state and year fixed effects. Standard errors are clustered at the state 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	0.45***	0.18**	0.35***	0.07
	(4.06)	(2.56)	(6.06)	(1.15)
High Flood Risk	0.16	0.17**	0.07	0.08
	(1.53)	(2.29)	(0.78)	(1.31)
Log(Population)	0.02	−0.06*	0.02	−0.02
	(0.35)	(−1.79)	(0.60)	(−0.57)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered s.e.	State	State	State	State
Observations	3,972	3,972	6,389	6,389
Adjusted R^2	0.15	0.19	0.10	0.14

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)	0.01*	0.01**	0.01	0.01*
	(1.77)	(2.34)	(1.61)	(1.66)
Log(Population)	−0.31	1.07	−2.16	1.36
	(−0.26)	(0.93)	(−1.03)	(0.89)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered s.e.	City	City	City	City
Observations	478	478	458	458
Adjusted R^2	0.81	0.85	0.73	0.80

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. Columns (1) and (2) report regressions using textual measures extracted from all document sources, while columns (3) and (4) report regressions using textual measures from budgets, and columns (5) and (6) report regressions using textual measures from bond prospectuses. *Exposure* is number of climate exposure sentences in all documents, scaled by the total number of sentences, winsorized at 1%, and standardized. *Adaptation* is number of adaptation sentences in all documents, scaled by the total number of sentences, winsorized at 1%, and standardized. *Republican* is an indicator variable equal to one if the city has a Republican mayor. *UFB/Total Expense* is unrestricted fund balance scaled by total expenses. *Total Debt per Capita* is total debt outstanding scaled by the population of the city. *Capital Budget Outlook* is the reported number of years in the capital budget. *Flood Risk* is the standardized percentage of properties at risk in a city. *Population* is the population of the city. We also include county-year fixed effects. Standard errors are clustered at the state level. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

	Dependent variable:					
	Exposure	Adaptation	Exposure	Adaptation	Exposure	Adaptation
	All		Budgets		Bond Prospectuses	
	(1)	(2)	(3)	(4)	(5)	(6)
Republican	-0.176^{*}	-0.292^{***}	-0.195	-0.245^{*}	-0.159^{**}	-0.330^{***}
	(-1.789)	(-2.869)	(-1.344)	(-1.928)	(-2.229)	(-3.609)
UFB/Total Expense	0.124^{*}	0.173	0.129	0.150	0.022	0.125
	(1.814)	(1.497)	(1.473)	(1.327)	(0.440)	(0.915)
Log(Total Debt per Capita)	-0.137^{*}	-0.189^{***}	-0.116	-0.196^{***}	-0.048^{*}	-0.142
	(-1.741)	(-2.761)	(-1.169)	(-3.956)	(-1.729)	(-1.062)
Capital Budget Outlook	-0.014	0.005	0.006	0.018	-0.006	0.012
	(-0.544)	(0.115)	(0.174)	(0.392)	(-0.334)	(0.629)
Flood Risk	0.021^{***}	0.019^{***}	0.016^{***}	0.023^{***}	0.019^{**}	-0.007
	(3.672)	(10.403)	(6.341)	(12.069)	(2.358)	(-1.284)
Log(Population)	0.051	0.038	0.104	0.120	-0.013	-0.003
	(1.169)	(0.402)	(0.966)	(1.212)	(-0.363)	(-0.023)
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered s.e.	State	State	State	State	State	State
Observations	2,032	2,032	1,999	1,999	1,423	1,423
Adjusted R^2	0.393	0.377	0.115	0.299	0.681	0.405

Table 6: Climate exposure and adaptation by local beliefs.
This table presents the associations between our textual climate exposure and adaptation measures and the city-specific characteristics. *Exposure* is number of climate exposure sentences in all documents, scaled by the total number of sentences, winsorized at 1%, and standardized. *Adaptation* is number of adaptation sentences in all documents, scaled by the total number of sentences, winsorized at 1%, and standardized. *Worried* is an indicator variable equal to one if 2014 residents' level of concern about climate change is above median, based on county-level Yale Climate Opinion Map data. *Republican* is an indicator variable equal to one if the city has a Republican mayor. *UFB/Total Expense* is unrestricted fund balance scaled by total expenses. *Total Debt per Capita* is total debt outstanding scaled by the population of the city. *Capital Budget Outlook* is the reported number of years in the capital budget. *Flood Risk* is the standardized percentage of properties at risk in a city. *Population* is the population of the city. We also include county-year fixed effects. Standard errors are clustered at the state level. t-statistics are reported in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

	Dependent variable:							
	Exposure	Adaptation	Exposure	Adaptation	Exposure	Adaptation	Exposure	Adaptation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Republican × Worried	0.816**	0.372**						
	(2.090)	(2.121)						
UFB/Total Expense × Worried			−0.237	0.255				
			(−0.683)	(0.641)				
Log(Total Debt per Capita) × Worried					0.179	−0.060		
					(0.666)	(−0.351)		
Capital Budget Outlook × Worried							0.195*	0.070
							(1.695)	(1.005)
Republican	−0.806**	−0.579***	−0.171	−0.297***	−0.174	−0.293***	−0.138**	−0.279**
	(−2.181)	(−6.448)	(−1.579)	(−2.907)	(−1.592)	(−2.887)	(−2.383)	(−2.545)
UFB/Total Expense	0.122*	0.172	0.322	−0.040	0.123*	0.173	0.117	0.170
	(1.737)	(1.505)	(0.958)	(−0.096)	(1.791)	(1.509)	(1.640)	(1.430)
Log(Total Debt per Capita)	−0.134	−0.188***	−0.139*	−0.187***	−0.269	−0.145	−0.130	−0.187**
	(−1.632)	(−2.858)	(−1.701)	(−2.816)	(−1.091)	(−0.833)	(−1.647)	(−2.663)
Capital Budget Outlook	−0.008	0.008	−0.015	0.005	−0.014	0.005	−0.166	−0.050
	(−0.374)	(0.185)	(−0.557)	(0.129)	(−0.542)	(0.114)	(−1.456)	(−0.979)
Flood Risk	0.020***	0.019***	0.021***	0.019***	0.021***	0.019***	0.021***	0.019***
	(4.521)	(10.466)	(3.496)	(9.323)	(3.574)	(10.421)	(3.641)	(10.302)
Log(Population)	0.063	0.044	0.051	0.038	0.045	0.040	0.044	0.036
	(1.331)	(0.458)	(1.174)	(0.409)	(1.007)	(0.435)	(1.065)	(0.382)
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered s.e.	State	State	State	State	State	State	State	State
Observations	2,032	2,032	2,032	2,032	2,032	2,032	2,032	2,032
Adjusted R^2	0.414	0.380	0.396	0.380	0.396	0.376	0.423	0.379

Table 7: Primary market tests: replication of Painter (2020).
This table presents a replication of the results of the Painter (2020) regression of equation (1). The dependent variable is the offering spread, defined as the difference between offering yield and the maturity-matched yield from the treasury curve. *Adaptation* is number of adaptation sentences in all documents, scaled by the total number of sentences, winsorized at 1%, and standardized. *Exposure* is number of climate exposure sentences in all documents, scaled by the total number of sentences, winsorized at 1%, and standardized. *Flood Risk* is the standardized percentage of properties at risk in a city. 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, competitively issued, federally tax-exempt, state tax-exempt, or subject to AMT. We also include state-year fixed effects. t-statistics are reported in parentheses, with standard errors clustered by county. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively. The number of bonds in this analysis is bigger than the number of bond prospectuses collected (Table 1) because each bond issue has multiple bonds and only one prospectus.

	Dependent variable:	
	Offering Spread	
	(1)	(2)
Adaptation		-0.03^{***}
		(-2.88)
Exposure		0.02^{**}
		(2.52)
Flood Risk	0.01	0.01
	(1.08)	(0.74)
Ln(Size)	0.05	0.05
	(0.25)	(0.24)
Ln(Maturity)	0.17^{***}	0.17^{***}
	(4.98)	(4.77)
Rating	0.06^{***}	0.06^{***}
	(7.88)	(7.84)
Callable	0.55^{***}	0.55^{***}
	(71.56)	(64.79)
Insurance	0.07^{**}	0.07^{**}
	(2.29)	(2.14)
Sinkable	0.18^{***}	0.18^{***}
	(9.08)	(7.17)
GO	-0.02	-0.02
	(-1.36)	(-1.33)
Pre-Funded	0.02^{*}	0.02
	(1.79)	(1.62)
Competitive	-0.07^{***}	-0.07^{***}
	(-3.43)	(-3.27)
Ln(CUSIPS/Issue)	-0.13	-0.13
	(-0.51)	(-0.50)
Ln(Underwriter Deals)	0.01^{*}	0.01^{*}
	(1.73)	(1.86)
Fed Exempt	0.70^{***}	0.70^{***}
	(35.04)	(32.68)
State Exempt	0.02	0.02
	(0.21)	(0.19)
AMT	0.35^{***}	0.35^{***}
	(8.44)	(8.67)
State-Year FE	Yes	Yes
Clustered s.e.	County	County
Observations	38,184	38,061
Adjusted R^2	0.72	0.72

Table 8: Secondary market 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, winsorized at 1%, and standardized. *Exposure* is number of climate exposure sentences in all documents, scaled by the total number of sentences, winsorized at 1%, and standardized. *Flood Risk* is the standardized percentage of properties at risk in a city. 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, 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 county and year-month. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

	Dependent variable:	
	Secondary Spread	
	(1)	(2)
Adaptation		-0.04^{*}
		(-1.67)
Exposure		-0.03
		(-1.67)
Flood Risk	0.06^{**}	0.09^{***}
	(2.53)	(3.42)
Log(Time to Maturity)	-0.0000^{***}	-0.0000^{***}
	(-3.11)	(-3.09)
City Average Income	-0.13^{***}	-0.13^{***}
	(-4.03)	(-3.91)
GO Bond	-0.06^{***}	-0.06^{***}
	(-7.54)	(-7.54)
Time from Issuance	-0.02^{**}	-0.02^{**}
	(-2.16)	(-2.20)
Trading Volume/Amount Outstanding	0.31^{***}	0.31^{***}
	(8.00)	(8.01)
SD(Monthly Transaction Prices)	-0.0001^{***}	-0.0001^{***}
	(-3.29)	(-3.29)
Insured $\times$ Year	-0.0000	-0.0000
	(-0.05)	(-0.05)
Callable $\times$ Year	-0.0001^{**}	-0.0001^{**}
	(-2.50)	(-2.51)
Trade-Month FE	Yes	Yes
Observations	177,674	177,674
Adjusted R^2	0.19	0.19

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:

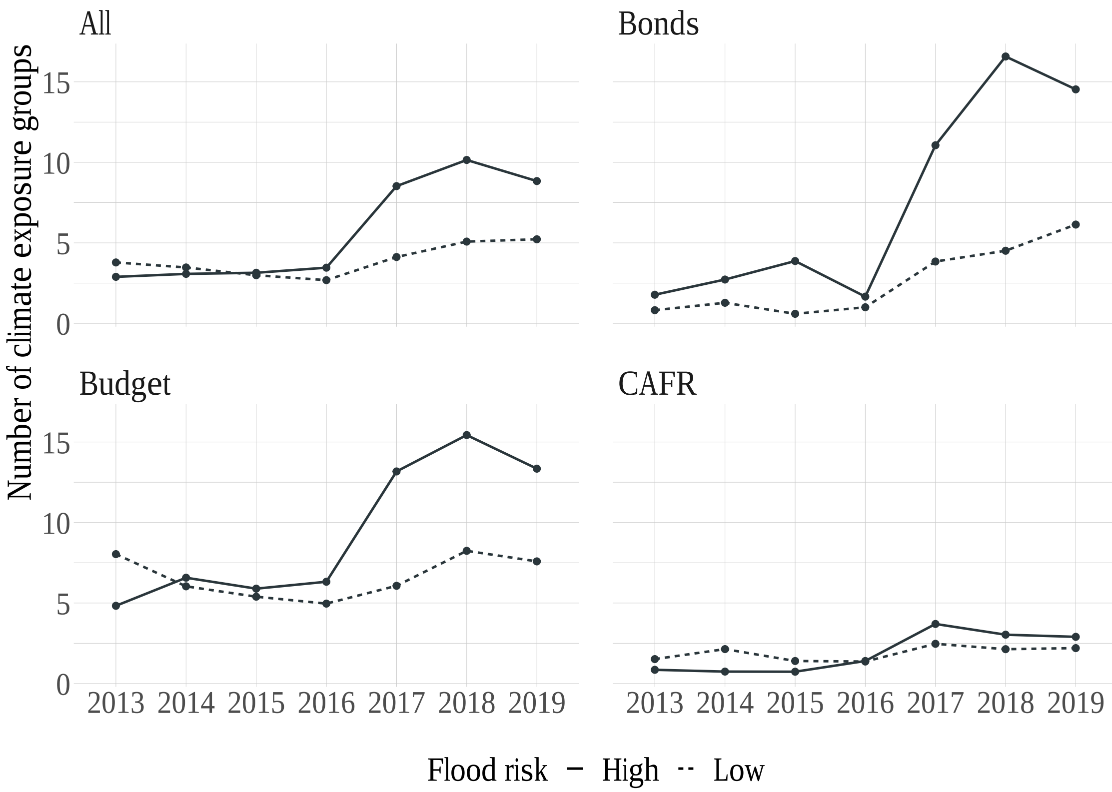
Not Applicable

	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

180

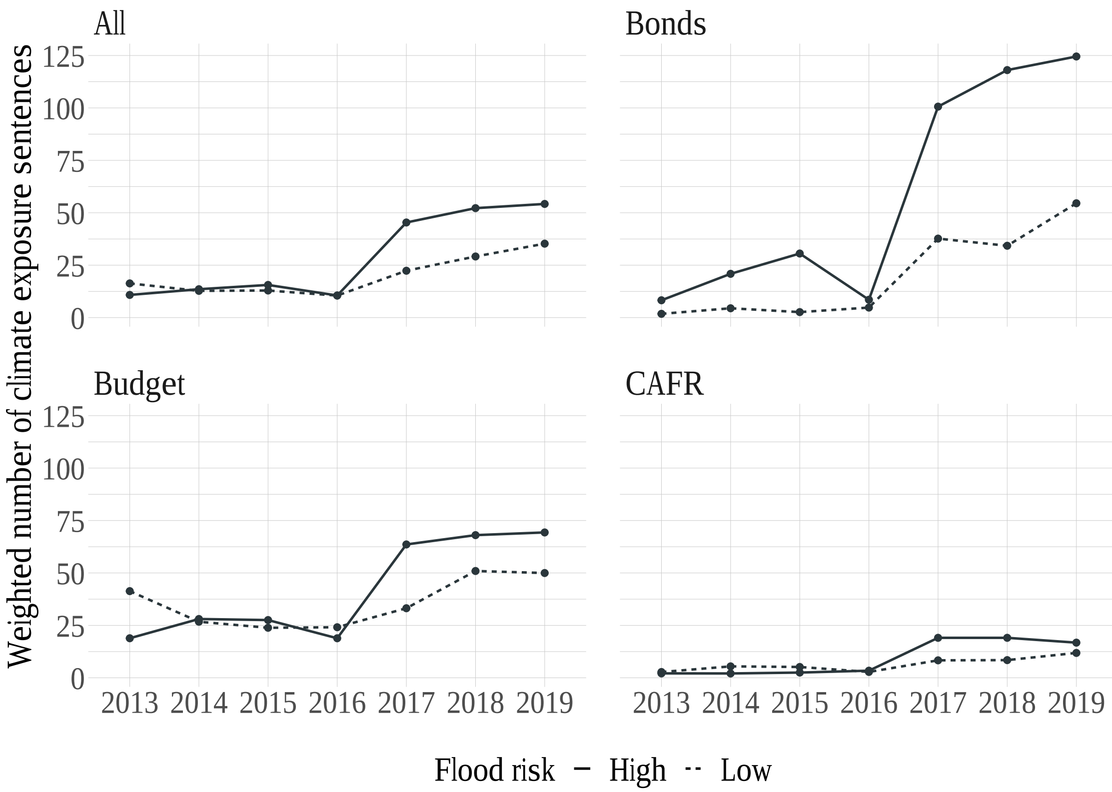
Appendix B.

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.



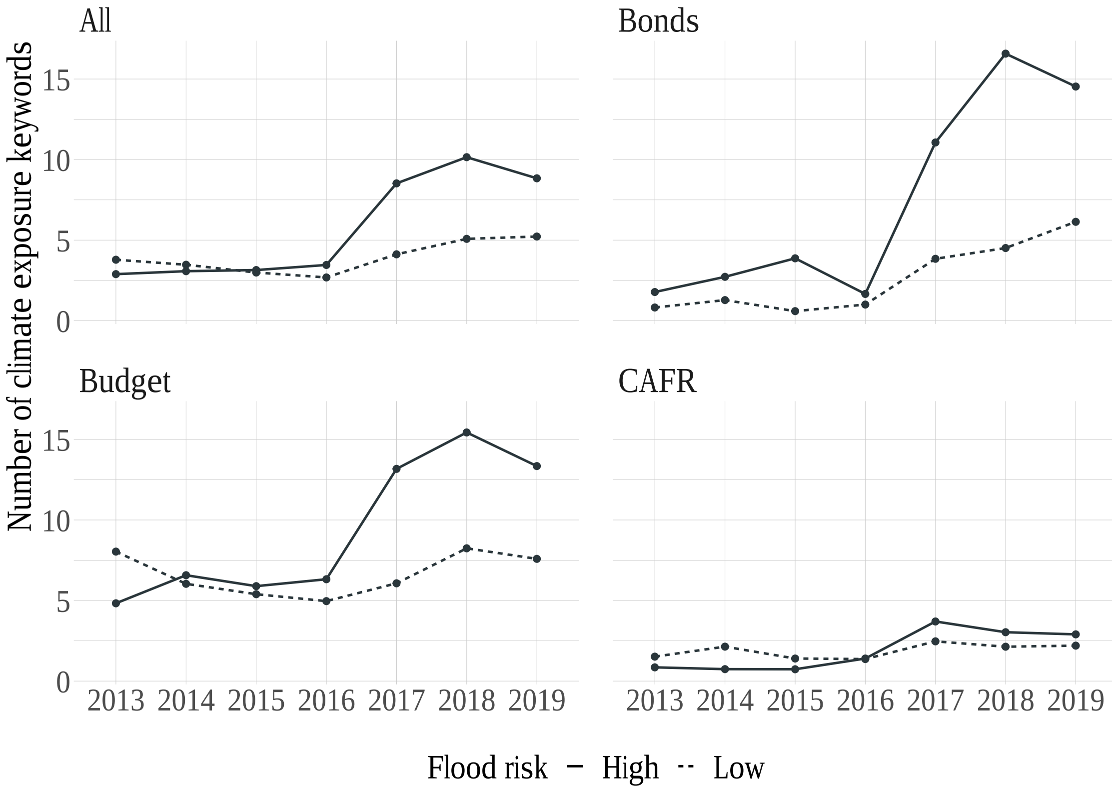
Appendix C.

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.



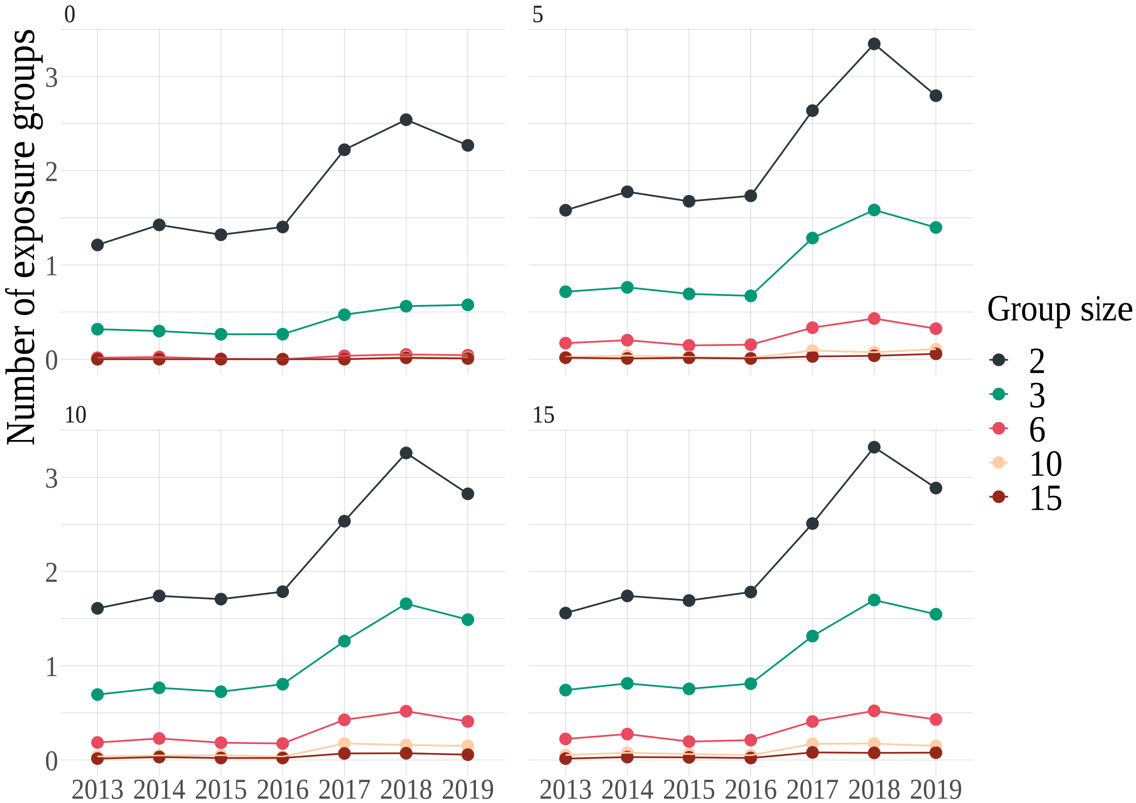
Appendix D.

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



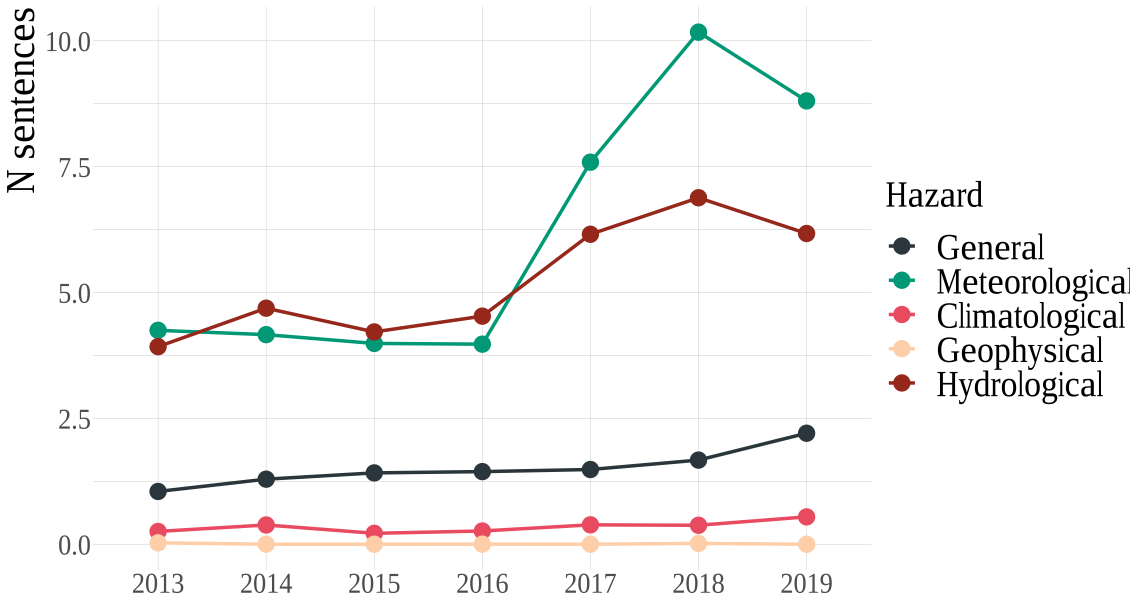
Appendix E.

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.



Appendix G.

Table G1: Relative frequency of exposure and adaptation words.
The table reports the relative frequency of the keywords used to create climate disclosure and adaptation measures.

Climate Exposure		Adaptation					
Keywords	Frequency	Keywords	Frequency	Keywords	Frequency	Keywords	Frequency
flood	27521	drainage system	10801	bioswale	319	flood assistance	48
hurrican	12916	flood control	9281	stormwater construction	316	storm hardening	48
wet weather	2938	seawall	5730	stormwater retrofit	313	wind mitigation	47
rain fall	2867	drainage project	5489	dikes	247	pervious pavement	44
tornado	2564	street drainage	5316	beach nourishment	242	tidal valves	43
sea level rise	1760	stormwater system	5295	breakwater	236	wind resistance	38
stormwater runoff	1627	inlets	4173	stormwater inspection	224	wind resistance	32
fog	1599	stormwater system	3290	retention pond	222	exfiltration system	31
storm event	1222	erosion control	2866	stormwater retention	204	sea level rise mitigation	31
storm damag	1043	drainage facilities	2590	flood prevention	201	stormwater catch basin	31
lightning	981	storm water infrastructure	2401	dike	196	drainage mitigation	29
tropical storm	789	stormwater services	2375	flood wall	194	improve road drainage	28
subsidence	778	stormwater project	2329	catch basin repair	174	sandbag	28
storm water runoff	691	improve drainage	2185	sea wall	172	earthen berm	24
rain event	659	stormwater operation	2096	retention basin	164	drainage evaluation	21
heavy rain	532	levee	1882	sand replenishment	160	StormReady	21
storm surge	464	stormwater operation	1784	hurricane preparedness	158	flood restoration	19
inundation	388	flood protection	1585	drainage rehabilition	135	surface water maintenance	15
rising sea levels	259	drainage infrastructure	1475	recharge wells	134	flood preparedness	13
SLR	228	improv stormwater	1431	wet pond	130	stormwater vault	12
high tide	170	flood mitigation	1316	stormwater equipment	126	drainpipe replacement	10
cyclone	132	project stormwater	995	rain garden	122	elevated roads	8
electrical storm	92	drainage channel	887	hurricane protection	110	shoreline maintenance	7
rain storm	87	stormwater master planning	779	shoreline protection	109	tidal control valve	6
typhoon	86	flood relief	738	dyke	103	ground water retention	5
king tide	72	pump system	735	living shoreline	101	rainwater capture	5
storm conditions	72	spillway	734	stormwater drain	98	detention storage systems	4
rainstorm	62	drain pipe	721	water channel	94	drainage line rehabilitation	3
saltwater intrusion	56	stormwater infrastructure	687	drainage replacement	88	sea level rise modelling	3
rain fall	49	stormwater collection	661	buyout program	84	stormwater evaluation	3
rising temperature	45	stormwater pump	652	dykes	82	stormwater inlet replacement	3
thunderstorm	42	National Flood Insurance Program	614	drainage well	73	stormwater conveyance retrofit	2
rise tide	32	storm water project	513	stormwater vaults	70	shoreline conservation	1
acid rain	30	stormwater pump station	507	sandbags	65	buyout programs	0
salt water intrusion	23	stormwater pond	491	stormwater capture	62	retention storage systems	0
tidal event	16	rain gardens	454	spillways	61	soil retention	0
extreme rain	13	flood management	421	prevention of flood	58	wet detention basin	0
extreme precipitation	9	flood mapping	418	raising streets	58		
severe wind	5	floodwall	408	stormwater quality improvement	58		
ocean acidification	2	stormwater compliance	363	drain pipe	57		
emperor tide	0	flood plain management	357	hurricane hardening	54		
storm catastrophy	0	stormwater administration	341	swale restoration	54		