Local Public Finance Dynamics and Hurricane Shocks

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Abstract

Since 1980, over 2,000 local governments in US Atlantic states have been hit by a hurricane. We study local government fiscal dynamics in the aftermath of hurricanes. These shocks reduce tax revenues, public expenditures, and debt financing in the decade following a hurricane. Hurricanes create collateral fiscal damage for local governments by increasing the cost of debt at critical moments after a strike. Municipalities with a 1 standard deviation-above-average racial minority composition suffer expenditure losses more than 2 times larger and debt default risk 8 times larger than the average municipalities in the decade following a hurricane strike.

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1 Introduction

Local governments are essential providers of public goods and services utilized by Americans every day. Sanitation, policing, parks and recreation, public transit, and street maintenance are a subset of the wide array of services primarily provided at the local level. In 2017, local government expenditures comprised 35% of the combined $15,541 spent by all levels of government per person on public goods and services.[1] To fund their operations, local governments rely on local tax revenues and debt, both of which depend heavily on the existence of a stable tax base. This paper examines how extreme weather events threaten the stability of these local revenue sources and the ability of municipalities to provide essential goods and services. While recent research has highlighted the substantial social costs that natural disasters impose through federal welfare programs (Deryugina, 2017), little is known about how extreme weather events impact municipal budgets in the US context. This gap in our understanding has important distributional consequences because local public services, such as transportation, welfare assistance, and public housing, are essential for lower income households (Glaeser et al., 2008; Feler and Senses, 2017) and because local governments with large racial minority populations are more likely to be exposed to extreme weather events. Taken together, these facts highlight that the costs of climatic natural disasters are often borne by those with the greatest needs (Banzhaf et al., 2019).

We provide new evidence that hurricanes jeopardize local provision of public goods. While prior research has shown that hurricanes lead to declines in personal income (Strobl, 2010; Anttila-Hughes and Hsiang, 2013), employment (Belasen and Polachek, 2009) and property values,[2] it is unclear whether such effects will lead to municipal budgetary losses. First, hurricanes may stimulate economic activity that can offset immediate fiscal shocks and even improve fiscal outcomes in the long term for local governments. Prior work shows that natural disasters can promote adoption of new capital stock (Skidmore and Toya, 2002), as well as increased demand for labor (Belasen and Polachek, 2009; Groen et al., 2016; Deryugina et al., 2018; Tran and Wilson, 2020). Second, local governments can generally rely on state reserve funds (Urahn and Irwin, 2020; Gregory, 2013) and federally-backed insurance like FEMA to pay for damages to physical property in the aftermath

[1] Based on per capita annual expenditures on education, health, housing, welfare, public safety, justice, and building maintenance. Federal expenditures sourced from Office of Management & Budget Historical Tables, and excludes expenditures related to national security, international affairs, science & space exploration, agriculture, Medicare, income and social security, veterans affairs, or general government administrative functions. Local and state expenditures sourced from Census of Governments.

[2] For instance, Hallstrom and Smith (2005), Davlasheridze et al. (2017), Ortega and Taşpinar (2018), Muller and Hopkins (2019), and Boustan et al. (2020).

of a hurricane (Garrett and Sobel, 2003; del Valle et al., 2019; Masiero and Santarossa, 2020). The availability of federally-backed flood insurance to home owners through the National Flood Insurance Program could also offset negative impacts on house prices or even increase property tax revenues if hurricane disasters stimulate housing re-development (Gaul, 2019; Liao and Kousky, 2022). Third, municipalities can leverage debt instruments in absence of tax-based revenue sources to fund capital investments and infrastructure. Our analysis indicates that such levers do not, on average, offset the contracting effects of hurricane exposure on municipal budgets in the long run. We document that hurricanes increase borrowing costs at critical moments after a hurricane strike. These results imply that hurricane-induced declines in current financial resources can translate into lower future investments.

We use novel data on municipal bond default risk to show that worsening debt ratings and declines in outstanding debt are an important reason local governments are unable to recover pre-hurricane budget levels in the 10 years following hurricane exposure. Previous work shows that severe natural disasters cause sustained out-migration (Vigdor, 2008; Strobl, 2010; Deryugina et al., 2018; Billings et al., 2022; Boustan et al., 2020). Our research provides new evidence that adverse shocks to municipal finances explain part of the reason populations do not return to areas affected by major hurricanes in their immediate aftermath. These findings, thus, highlight how natural disasters not only generate direct costs on local governments through necessitating reconstruction and assistance payments, but indirect costs by disrupting local revenue sources and increasing the cost of public debt.

Using the universe of Atlantic Basin hurricanes that made landfall in the United States between 1972 and 2017, we estimate how a municipality's budget, tax base, and debt financing evolve in the decade following exposure to hurricanes. We develop a granular hurricane exposure measure based on maximum wind speed at the level of the census tract in order to capture variation in treatment at the municipality level. In a panel fixed effects framework, we compare municipalities exposed to hurricanes against those—within the same state—that are not exposed to estimate how hurricanes affect municipal budgets. The impacts of hurricanes can vary widely across space, thus a localized exposure measure combined with municipal-level outcomes can accurately capture economic costs of hurricanes where more coarse geographic exposure measures generally underestimate such costs (Bertinelli and Strobl, 2013).

Our empirical approach exploits the random timing of hurricanes at the municipal government level. We compare municipalities within the same state that are demographically and geographically similar, but differ in hurricane exposure by chance. Because municipalities and credit rating agencies cannot accurately predict within a year's time when and where future hurricanes will strike, we are able to interpret post-hurricane changes in finances as a causal result of hurricane exposure. Our approach removes variation across municipalities with differing geographic risk, for instance coastal versus inland locations, and instead relies on the fact that local officials cannot precisely predict if a hurricane will strike before fiscal decisions are made for the next year.

Our analysis provides two key findings. First, local governments experience significant declines in aggregate revenues, expenditures, and debt in the 10 years after a hurricane strike. These declines are initially offset by intergovernmental transfers in the immediate aftermath of a hurricane but manifest significantly after 6–10 years post hurricane. Local revenue sources, including taxes and fees, fall up to 2% in the 6–10 years after exposure. The effects from major hurricanes are over twice as large as that of the average storm: we find major hurricanes reduce aggregate local revenues by 7.2% in the decade following a hurricane. The magnitude of this effect is economically large, matching the average amount taxpayers spend annually on state and local government employee payroll (Novy-Marx and Rauh, 2014).[3] Local revenue declines cause subsequent declines in local public goods provision: expenditures on aggregate public works including water, sewer, trash, and public transit, decline by 3.4% in the 6-10 years after exposure. Major hurricanes cause significantly more service disruption: local public works expenditures decline 13% after exposure to a hurricane with a maximum wind speed exceeding 96 knots. The fact that aggregate expenditures decline nearly in tandem with revenues is consistent with prior work on local budgetary responses to local tax revenue shocks.[4]

Per capita, we find smaller and less significant declines in total revenues and expenditures in the 6 to 10 years after exposure, suggesting per person service provision is unchanged. However, we find significant declines in own-source revenues per capita of 1.3% and public works expenditures per capita of 2.6%. This finding underscores that local governments have less capacity to provide goods with large fixed costs following a hurricane strike. Furthermore, municipalities become increasingly reliant on intergovernmental transfer income to maintain their per capita levels of service provision

[3] Novy-Marx and Rauh (2014) find that annual expenditures on payroll for state and local public sector employees amounts to $5,450 per household, on average (Table 1). Our estimates translate to a decline of $5,161 per household (based on total own revenues and population counts as of 1982 among municipalities ever hit by a hurricane between 1972 and 2017 and assuming three people per household).

[4] For instance, see Lutz (2008), Skidmore and Scorsone (2011), Lutz et al. (2011), Alm et al. (2011), Cromwell et al. (2015), Feler and Senses (2017), Melnik (2017), and Shoag et al. (2019).

after a hurricane.

We additionally find that aggregate total debt falls by 19.2 to 25.9% in the 10 years following a major hurricane. Unlike tax-based revenue sources, the availability of debt declines immediately after hurricane exposure, and persists up to a decade thereafter. We find that part of the decline in municipal debt is caused by responses of ratings agencies. On average, Moody's Analytics—one of the three largest ratings agencies in the world—downgrades bond ratings in the aftermath of a hurricane. These downgrades translate into a 17% increase in the risk of default relative to the sample standard deviation in each of 10 years after a hurricane strike. Using a "neighboring municipality" analysis that compares hurricane exposed municipalities to neighboring municipalities that nearly miss exposure to the same disaster, we find evidence that Moody's downgrades municipal debt following hurricane strikes due to declines in local economic conditions rather than perceptions of climate risk. Our analysis on municipal debt fits into a growing body of literature that explores how natural disasters affect financial markets (for example, Lamb 1995, Ouattara and Strobl 2013, Unterberger 2018, Krueger et al. 2020, Painter 2020)[5]. Our paper contributes to this literature by combining granular hurricane exposure measures with local-level public finance outcomes. This exercise produces notably different conclusions from prior studies on hurricanes because we show that local-level governments suffer losses following storm exposure. We show that aggregated county or state-level analyses mask these local negative impacts.[6]

The second key finding is that we find greater losses of revenues and public goods expenditures among local governments that historically have populations that are poorer, less educated, and contain higher shares of racial minorities. We find that a one standard deviation increase in the 1970 non-white population share exacerbates revenue declines by an additional 1.3% in the decade after a hurricane, or more than double the impact on municipalities with an average 1970 racial composition. Importantly, we find treatment effect heterogeneity across municipalities using only within-state variation, implying that regional demographic differences across municipalities in our sample cannot explain the disproportionate losses suffered by local governments that are majority nonwhite or low-income.

Most prior studies have found limited heterogeneity across demographic groups in the impacts of hurricanes on personal welfare outcomes (Deryugina et al., 2018; Deryugina and Molitor,

[5]We discuss this literature in greater detail in Section 5.3

[6]A recent working paper by Noy et al. (2021) finds similar patterns from earthquake exposure in Japan. Regional governments do not incur fiscal losses, but local governments reduce budget shares in public services.

2020; Groen et al., 2020). Recent work by Billings et al. (2022) provides an important exception. They find that credit delinquency rates were higher following Hurricane Harvey among residents that were less likely to own homes relative to home owners. They also find that individuals living on blocks with more nonwhites or low-income residents were less likely to receive FEMA assistance. Because local tax revenues are tied to housing values, the unequal effects of Hurricane Harvey on individual finances documented by Billings et al. (2022) may be one mechanism driving the unequal impacts of hurricanes on local public finances documented here. Our paper provides evidence that declines in municipal budgets comprise a channel by which hurricane damages can be regressive. The disproportionate impact on municipalities with a higher proportion of low-income and minority residents is particularly concerning because these groups tend to be more reliant on public services (Betts and Fairlie, 2001; Glaeser et al., 2008) and thus more likely to be harmed by weakened municipal finances. In fact, we show that hurricane exposure serves to change the demographic composition of municipalities toward more impoverished populations. We find that hurricane exposure marginally increases local poverty rates as well as the non-white population share in the decade following exposure. These findings suggest that, while per capita revenues and expenditures do not change significantly, incumbent populations may be worse off on average following hurricane exposure because remaining residents are more likely to require public services and assistance.

Our results illuminate how disruptions in local provision of goods and services are an additional economic cost for those with the least ability to cope with natural disaster risk. Our analysis of the recent past is relevant for considering a future with more frequent and high-intensity hurricanes (Kossin et al., 2020) as we show that fiscal costs are disproportionately borne by minority and lower-income communities.

This article proceeds as follows. Section 2 discusses the theoretic predictions that motivate our empirical approach. In Section 3, we discuss the construction of our data set including our localized measurement of hurricane exposure. Section 4 explains our empirical approach. We present our main results on local revenues, expenditures, default risk, and debt in Section 5. We discuss both aggregate and per capita changes following hurricane exposure. Here, we consider mechanisms driving ratings agencies to adjust bond ratings, and distinguish between mechanical destruction to local economic conditions and updates to agency perceptions of ex ante hurricane risk. In Section 6, we show how the affects of hurricanes vary by socio-economic conditions across municipalities, suggesting that the local fiscal costs of hurricanes have important distributional consequences. Section 7 shows the results of several robustness checks, including specification checks, pre-trend analyses, and sampling restrictions. Finally, Section 8 concludes.

2 The Municipality's Budget Constraint & Resource Allocation Problem

Our empirical work examines how local public finances evolve in the aftermath of major natural disasters. A straightforward examination of income effects and substitution effects offers several insights about the empirical patterns we document below.

At any point in time, a stylized version of a local government's intertemporal budget constraint (with time subscripts omitted) can be written as

$$E + rB = R + G + \Delta B \tag{1}$$

where E, r, B, R, G, and ΔB are total expenditures (including current expenses and capital outlay), interest rate, government debt (bonds), own-source revenues, intergovernmental transfers, and new bond issuance. Changes in total expenditures are determined by how hurricanes affect each component of governments' budgets. Total differentiating Equation 1 with respect to an exogeneous shock x and collecting terms yields

$$\frac{dE}{dx} = \frac{dR}{dx} + \frac{dG}{dx} + \frac{d\Delta B}{dx} - \left(r\frac{dB}{dx} + \frac{dr}{dx}B \right). \tag{2}$$

First, the impact on own-sourced revenues are determined by how hurricanes affect the tax base and the tax instruments that cities use to raise revenues. Holding tax rates constant, a city's revenues will fall if the tax base shrinks due to outmigration (loss of human capital) or destruction of physical capital. In this case, hurricane-hit cities experience a pure negative income shock: $dR/dx < 0$. When cities can adjust local tax rates, the sign of dR/dx depends on the revenue elasticity with respect to the tax instruments used.

Second, when natural disasters are sufficiently severe, the negative fiscal effects of hurricanes can be offset by an increase in intergovernmental transfers: $dG/dx > 0$. For example, when major natural disasters that trigger Presidential Disaster Declarations mobilize federal programs, such as FEMA's Public Assistance program, state and local governments can be reimbursed by the federal government anywhere between 75 to 100% of the costs of approved projects. While these grant distributions can be discretionary, motivated by political connections or popular press coverage (Garrett and Sobel, 2003; Eisensee and Strömberg, 2007), federal appropriations for disaster relief have grown by a factor of eight since the Stafford Act of 1988 from \$1 billion to over \$8 billion today (Stein and Van Dam, 2019).

Third, severe natural disasters can influence local government debt through three key channels. The first channel is the effect of natural disasters on new debt issuance ($d\Delta B/dx$). The second channel is how hurricanes impact total debt outstanding through debt retirement and defaults (dB/dx). The third channel through which natural disasters can impact debt is capital market's assessment of municipal bond default risk, which is reflected in a city's bond ratings (dr/dx). Low bond ratings and high interest rates can deter local governments from engaging in debt financing. If a city's default risk increases as a result of a shock, the city experiences a "substitution effect" in addition to an income effect as higher capital prices hinder their ability to make key infrastructure investments.

Together, the income and substitution effects of natural disasters can lead to a vicious cycle in which cities' *current* shrinking budgets translate into lower *future* investments and public good provisions, leading to further fiscal declines and delayed capital investment. All three of the channels discussed above—debt issuance, debt retirement and debt outstanding, and the default risk associated with new debt—are important for governments that need to rebuild infrastructure harmed by natural disasters or invest in new mitigation technologies like pumps or levies. These capital investments at a current period can ultimately affect the relative attractiveness of a city to a marginal mover in a future period and the city's ability to return to it's pre-hurricane economic growth path (Haughwout, 2002; Albouy and Farahani, 2017; Jerch, 2020).

As municipal budgets adjust to natural disasters, local officials must decide how to allocate scarce funds (dE/dx). Such decisions are complicated by differential public good utilization across the tax base and incentives of local officials. For instance, Figure 1 shows that among local governments within Atlantic states, a higher share of non-white residents, a higher share of residents with earnings below the poverty line, and a higher share of population with less than high school education are all associated with higher expenditures shares in important public services such as local health, housing, welfare assistance, and transportation. These correlations are consistent with prior work showing that minority and low-income households are more likely to attend public school (Betts and Fairlie, 2001) and utilize public transit (Glaeser et al., 2008).

On the one hand, cities could raise taxes to repair and replace damaged physical capital and risk the loss of high-income residents who may relocate to avoid tax increases. On the other hand, cities could cut back on public goods and services, such as reducing the number of bus routes or scale back public education spending. Such actions would increase the incidence of hurricanes' fiscal effects on low-income households who have a relatively low migration rate and are highly reliant on local public goods (Molloy et al., 2011).

Besides fiscal considerations and distributional concerns, political incentives can influence how local governments re-optimize spending with respect to budget changes. For example, at the local level, city officials who seek reelection have incentives to allocate funds towards projects that have a short time horizon, high visibility among voters, and high political returns (Healy and Malhotra, 2009). At the federal level, disaster relief payments may also be politically motivated. For instance, Garrett and Sobel (2003) provide suggestive evidence that federal transfers are linked to the strength of the political affiliation between the president and a state's representation in Congress.[7] The broad menu of potential responses by local leaders highlights the theoretical ambiguity in hurricanes' fiscal impacts on local governments and the importance of testing for heterogeneous effects across spending categories and local resident attributes. We will discipline our exploration of such differential effects by focusing on how low-income, minority cities respond to disasters.

In studying the local consequences of hurricane exposure over a decade, we recognize that there are several interdependent mechanisms at work. Hurricane shocks can have a direct effect on injuring the tax base as owners of destroyed homes and businesses choose to move away. Hurricane shocks can also have an indirect effect on injuring the tax base: exposed populations may move away or marginal movers may choose less risky locations because they expect that prior hurricane shocks will have persistent negative effects on local public goods provision. This logic suggests that it is very difficult to tease out the direct effects separately from the indirect effects using our observational data. While we cannot conclude that declines to the local tax base cause declines in local economic conditions documented in prior literature, our findings underscore that these two outcomes are closely linked and that hurricane effects on municipal borrowing costs hamper local recovery efforts, particularly in minority and poor communities.

3 Data Description

We construct a balanced panel of public finance outcomes and hurricane exposure from 1982 through 2017 for 6,144 municipal governments. We choose this time window to strike a balance between

[7] In all our analysis, we exploit within-state variation to identify hurricanes' fiscal impacts so any biases resulting from this type of political process should be small.

having enough power to identify both short and long-term hurricane effects across several local governments, while including controls for pre-existing growth trends. Our "treatment unit" is the municipal government. By conducting the analysis at the municipality level, we allow for potential heterogeneous fiscal impacts across municipalities within the same county. We focus on municipal governments in the 21 states along the coasts of the Atlantic Ocean and Gulf of Mexico because the geography of these "hurricane states" make them prone to tropical storms and hurricane-strength winds from the Atlantic Basin.[8] Non-coastal states face limited hurricane exposure and do not constitute a good comparison group. Our municipal-level analysis requires three main types of data: local government finances, municipal demographics, and a measure of hurricane exposure.

3.1 Local Government Finance Data

We utilize the Census of Governments dataset as our source for annual local government revenues, expenditures, and debt. The survey is collected every five years, on years ending in "2" or "7" starting with 1967. The Census of Governments dataset is ideally suited for our purposes, as it contains the most comprehensive information on local public finances and employment across time and space. While this dataset includes both general-purpose governments (county, municipal, and township governments) and special-purpose governments (special-district and school-district governments), we focus on municipal governments because they perform relatively similar functions, even across states (e.g., providing public transportation to local residents). We report the results for the other local government types in Appendix B.12.

We track local government revenues from two main sources: own-source revenues and intergovernmental transfers. Own-source revenues are mainly comprised of property, sales, and income taxes.[9] Additional own-source revenues ("other revenues" hereinafter) come from miscellaneous revenues, user charges, and taxes on liquor stores and utilities. Intergovernmental transfers include funds from other governments, such as the federal, state, and other local governments. These revenue sources are allocated among a number of expenditure categories. We focus on the four largest expenditure shares: public works (48%), public safety (18%), miscellaneous expenditures (15%), and government administration (15%).[10]

[8]The list of states includes Alabama, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, Vermont, Virginia, and West Virginia. While Hawaii and California have experienced Pacific hurricanes, we exclude municipalities from these states because of significant regional and economic differences relative to Atlantic states.

[9]Other tax categories include license taxes and other miscellaneous taxes.

[10]We study the remaining two categories, public assistance (2%) and public education (2%) in the Appendix. The

We drop municipal government-year observations if any of the following outcomes are missing: revenues from all sources, total expenditures, and municipality population. Between 1982 and 2017, the sample includes 49,152 total observations, or 6,144 municipalities each observed in 8 years. Because a single hurricane can impact several local governments simultaneously, in some specifications we aggregate local public finance outcomes to the county-government type level. This aggregation ensures that our estimates of the impact of hurricanes on local public finances account for any intergovernmental transfers between local governments that perform similar functions within county jurisdictions.

3.2 Demographic and Economic Data

We collect data related to demographic and economic outcomes from several sources. We use data on municipalities' 1970 attributes from the National Historical Geographic Information System (NHGIS) to adjust for pre-hurricane differences in local characteristics. Because 1970 is the first year that municipality-level census data is available from NHGIS, we select 1982 as the first year to observe financial outcomes from the Census of Governments because this allows us to include "baseline" demographic and economic controls that are observed at least a decade prior to our financial outcomes of interest. The NHGIS municipal characteristics include (log) population, (log) land area, (log) distance to the nearest coast, share of population who are non-white,[11] share of population that are at least 25 years and have less than a high school education, and poverty rate.[12] We also collect annual data on county population and employment from the Bureau of Economic Analysis (BEA) and home value index for single-family homes from Zillow to conduct event study analyses.

3.3 Hurricane Data & Construction of Hurricane Exposure Index

We construct a dataset of city-level hurricane exposure using the Best Track Data from the Atlantic Hurricane Database (Atlantic HURDAT2). Our sample covers all storm events that reached hurricane-strength winds (at least 64 knots) between 1972 and 2017. The data set contains the location (latitude and longitude) and wind speeds of storm events at six-hour intervals. We cre-

complete list of government expenditures can be found in Appendix A.

[11] "Non-white" includes both hispanic and non-hispanic ethnicities.

[12] The 1970 Census does not report demographics for many municipalities with populations below 10,000 (around 37% of our sample). For municipalities with missing 1970 demographics, we interpolate their 1970 values using the 1980—2010 decennial census data from NHGIS. The non-interpolated 1970 values are highly correlated with the 1980 values, with correlation coefficients at least 0.87 and often much higher (between 0.94 and 0.98). As a robustness check, we re-estimate our results using a balanced panel of municipalities with non-interpolated 1970 controls in Appendix Table B.10. Our conclusions remain unchanged using the smaller sample.

ate hurricane tracks at 15-minute intervals by interpolating hurricane location and wind speeds between consecutive observations using a third-order polynomial.[13] Figure 2 uses the path of Hurricane Harvey in 2017 as an example to illustrate the relationship between a hurricane's track and the wind speed observed across exposed counties.

Using the interpolated hurricane tracks, we construct a hurricane exposure measure based on wind speed. The hurricane exposure measure captures two key aspects of the wind speed-property damage relationship: only wind speeds above a certain threshold produce physical damage, and extremely high wind speeds result in catastrophic damages (Emanuel, 2011). Following recent work by Hsiang and Jina (2014), Elliott et al. (2015) and Mahajan and Yang (2020), we assume that physical damage is a non-linear function of cubed maximum wind speed and no damage is caused by wind speeds below the 50 kt threshold.[14] We prefer this continuous measure to alternative measures, such as a binary indicator for hurricane exposure, because the measure captures more variation in local exposure to hurricanes. We employ alternative measures of hurricane exposure as robustness checks, such as linear and non-linear functions of wind speed, squared and cubed wind speed, and a binary indicator for a hurricane strike.[15] An important caveat of our exposure measure is that it does not all potential physical damages from hurricanes. For instance, flooding and storm surge can occur even with relatively low wind speeds. In practice, this means that our estimates are attenuated toward a null effect because fiscal damages may be large even in areas that experienced low or less than hurricane-strength wind speeds.[16] However, we include topographic controls like elevation, distance to coast, and land area interacted with time fixed effects in all regression analyses in order to account for differences across municipalities in their vulnerability to storm surge or flooding from a hurricane.

3.4 Geographic & Demographic Variation in Hurricane Exposure

We plot the geographic distribution of aggregate hurricane exposure between 1972 and 2017 in Figure 3. Panel A shows that counties in coastal Louisiana, North Carolina, and Florida experienced

[13] Emanuel (2005) notes that the power dissipation of hurricanes, which is a measure of storms' energy and potential physical impact, rises at roughly the cube of the maximum observed wind speed.

[14] Appendix A contains greater details on the construction of our exposure index.

[15] Our main exposure measure abstracts from weighting by population exposed or accounting for building vulnerability because such attributes can adjust to climate shocks over time.

[16] As far as we are aware, granular data extending back to the 1980's on, either, storm surge or past flood events are unavailable. Recent work by Irish et al. (2008) shows that storm size —measured as radius to maximum wind speed —is positively correlated with storm surge. They find that as much as 30% of the variation in storm surge can be explained by storm size. We were unable to measure damages using storm size rather than wind speed, however, because HURDAT2 (our source for hurricane wind speeds) began reporting storm radius data only in 2021.

the highest frequency of hurricane strikes over the sample period. Panel B plots the distribution of maximum wind speeds between 1972 and 2017 by county. Most counties along the Gulf Coast and along the Atlantic Coast south of Virginia experienced at least one major hurricane with wind speeds over 96 knots at some point over this 45 year period.

Table 1 compares mean characteristics across municipalities exposed to any hurricane between 1972 and 2017 with those not exposed. Despite using only municipalities located in hurricane states in our sample, we observe significant differences. Hurricane municipalities have larger revenues, larger expenditures on all service categories, and larger debt loads compared to non-hurricane municipalities. Hurricane municipalities also have, historically, larger populations that are more educated with higher poverty rates and a higher share of non-white residents. Noteably, areas with an historically higher composition of non-white residents are more likely to experience hurricanes, both, at a national level and at a regional level.[17] Thus, the racial difference in hurricane versus non-hurricane exposed municipalities is not solely explained by the higher share of non-white population in the Southeast. Hurricane municipalities have slightly lower default risk (higher average bond ratings), possibly due to their larger tax revenues and population size.

These cross-sectional differences in municipal characteristics are not necessarily problematic for our panel fixed effects approach as long as the differences are time-invariant. However, such differences in levels may portend differences in trends. Larger municipalities may afford greater access to and utilization of financial markets over time or may be privileged with greater federal and state aid. Such dynamics could confound our results. We try to minimize the possibility of differential trends across hurricane and non-hurricane municipalities in several ways. First, we control for municipal characteristics measured as of 1970 interacted with year indicators in all specifications. Second, we estimate "event study" specifications when data availability allows in order to observe evidence of pretrends. When data availability is more limited, we directly estimate whether current fiscal outcomes are affected by future hurricane exposure. Third, we conduct several robustness checks to account for differential trends including: controlling for municipality fixed effects interacted with a linear time trend, restricting our sample to only "cities" with larger populations, and employing a propensity score matching approach where we compare outcomes

[17] Based on the authors' analysis comparing average exposure to hurricane events from 1982-2017 among municipalities that differ based on their 1970 demographic composition. Specifically, we measure $y_{ist} = \beta^{NW} NW_{is1970} + \alpha_s + \varepsilon_{ist}$ weighted by 1970 population, where y_{ist} is a binary variable equal to 1 if municipality i experiences a hurricane in year t; NW_{is1970} is the share of the population in location i that are non-white as of 1970, and α_s is a state fixed effect. We find $\beta^{NW} = 0.35$, or municipalities with 10 percentage point greater composition of non-white residents experience approximately 3.5 percentage point increase in the risk of hurricane exposure.

across treated and control municipalities with very similar 1970 characteristics. We describe these results in greater detail in Sections 5 and 7.

4 Estimating the Local Fiscal Effects of Hurricanes

We estimate a panel fixed effects econometric model that relates outcomes of interest to local hurricane exposure. Our baseline econometric model is the following:

$$y_{ist} = \beta_1 H_{it}^{1-5} + \beta_2 H_{it}^{6-10} + \alpha_i + \alpha_{st} + \delta'(\mathbf{X}_i \alpha_t) + \varepsilon_{ist}, \tag{3}$$

where y_{ist} is an outcome in municipal government i in state s and year t.

The treatment effects H_{it}^{1-5} and H_{it}^{6-10} measure hurricane exposure in municipality i over years $t-1$ to $t-5$ and over years $t-6$ to $t-10$, respectively. For ease of interpretation, we normalize the hurricane exposure measures by their standard deviation. The parameters of interest, β_1 and β_2, capture the effect of a one standard deviation increase in hurricane-strength wind speed experienced in the past $t-1$ to $t-5$ and $t-6$ to $t-10$ years, respectively, on municipality i's outcome y observed in year t. Following prior literature (Deryugina, 2017), these coefficients distinguish between hurricanes' short-term effects (1 to 5 years after exposure) from their long-term effects (6 to 10 years after exposure) by measuring the maximum wind speed experienced by a municipality over the course of each period. As a robustness check, we control for potential persistence of a hurricane's effects by including an indicator for the occurrence of hurricane-strength winds in the previous decade, from $t-11$ to $t-20$.[18]

In Equation 3, we control for time-invariant municipal government unobservables and state-specific shocks by including municipal government fixed effects (α_i) and state-by-year fixed effects (α_{st}), respectively. The municipality fixed effects (α_i) account for the fact that localities historically more prone to hurricanes may have compositional differences in their public expenditures, like higher expenditures on infrastructure, for example. These fixed effects also remove any geographic differences across municipalities, like elevation and proximity to barrier islands, that create differential vulnerability to storm damages or storm surge. State-by-year fixed effects (α_{st}) account for time-varying state-level factors that impact a municipality's budget, like state fiscal shocks, state balanced budget rules, or state representation in US Congress.[19] We allow municipalities

[18] Data limitations prevent us from identifying effects over 10 years after exposure. Longer-term treatment effects are difficult to interpret due to (1) increased time-wise heterogeneity in the effects of hurricanes and (2) increased likelihood of conflating partial effects from cumulative effects. Most municipalities in our sample are struck by only one major storm, or multiple major storms within quick succession, within a decade. Consequently, we are able to interpret our parameter estimates as the total impact of one particular hurricane event in the 1-5 or 6-10 years after exposure.

[19] By using state-by-year fixed effects, our estimates do not capture any state-level shocks created by hurricanes

to exhibit differential trends by interacting a vector of initial characteristics measured as of 1970 ($\mathbf{X}_i$) with year fixed effects (α_t). The vector includes geographic and topographic features, such as land area and distance to the nearest coast, as well as the set of social and economic covariates discussed in the previous section (share of non-white population, share of population over the age of 25 without a high school degree, poverty rate, and log population). Regressions are weighted by the 1970 population.[20] Standard errors are clustered at the county level. In Appendix B.10 we apply spatially clustered standard errors that allow for spatial correlation of up to 200 kilometers around a municipality's centroid following Conley (1999). Our conclusions are unchanged if we cluster by county or allow for this more flexible spatial correlation.

Our measure of hurricane exposure is plausibly exogenous to local economic confounders for several reasons. First, our measure is based on meteorological data (wind speeds), which makes it less likely to suffer from changes in local economic activity compared to exposure measures based on physical or economic damages. Second, unless local governments or ratings agencies can accurately and consistently predict when a hurricane will make landfall and the amount of damage the landfall will inflict, it is unlikely that changes in local public finance outcomes or debt ratings following a natural disaster are due to local growth or fiscal decisions prior to the natural disaster. In Section 7, we support this assumption by showing that changes over time in local economic conditions and debt ratings do not predict future hurricane exposure.

In addition to estimating the average impact of hurricane exposure, we also test for heterogeneous effects by hurricane severity. We follow the literature (e.g., Deryugina, 2017) in using the maximum wind speed experienced between $t-1$ and $t-5$ and between $t-6$ and $t-10$ to separate hurricanes into "minor hurricanes" (Category 1–2 hurricanes with winds at least 64 kts and below 96 kts) and "major hurricanes" (Category 3–5 hurricanes with winds 96 kts or above). Specifically, we estimate:

$$y_{ist} = \delta_1 Min_{it}^{1-5} + \delta_2 Min_{it}^{6-10} + \kappa_1 Maj_{it}^{1-5} + \kappa_2 Maj_{it}^{6-10} + \gamma_t'(\mathbf{X}_i\alpha_t) + \alpha_i + \alpha_{st} + \varepsilon_{ist} \quad (4)$$

Min and Maj are indicators equal to 1 if the maximum wind speed experienced by a

such as reductions in state government transfers to all local governments. Our conclusions remain qualitatively similar for specifications that use only state fixed effects, however the effect sizes are generally larger in magnitude. This implies that hurricane exposure leads to aggregate reductions in state transfers to affected local governments, causing larger declines in revenues and expenditures in absolute terms. These results are available upon request.

[20] We weight by population because small municipalities are much more likely to have missing outcomes. Among municipalities in the Census of Governments, those with at least one missing expenditure outcome have a mean population of 1,270.19 whereas those without any missing expenditure outcomes have a mean population of 14,522.88, respectively.

municipality in the five-year intervals t_1 to $t-5$ and $t-6$ to $t-10$ is a minor or major hurricane, respectively. Thus the δ and κ parameters provide non-parametric estimates of the impact of any type of hurricane that falls into either of these two categories. All controls and fixed effects of Equation 4 mimic those in Equation 3. Standard errors are clustered at the county level, and all regressions are weighted by the local government's 1970 population.

5 Results

Our empirical tasks are threefold: first, we identify the magnitude of direct fiscal costs to the average municipality by examining changes in revenue and expenditure items following hurricane exposure. We calculate hurricane exposure at time t using the maximum hurricane-strength wind speed experienced by a municipality in the prior decade. Second, we test how hurricanes impact future capital investment capabilities by estimating differences in debt levels and bond default risk following exposure, and find evidence that both outcomes fall significantly in the decade following major storms. We supplement these findings with an exploration of the mechanisms that drive ratings agencies to alter municipal default risk. Our approach uses a "neighboring municipality" design, where we utilize municipalities that barely miss exposure to major hurricane-strength winds as a comparison group. Our results are suggestive that ratings agencies downgrade bond ratings due to the negative economic shock caused by hurricanes; as opposed to changes in ex ante risk perceptions of local government debt. Lastly, we document how these direct fiscal costs and long-term investment costs from hurricanes are substantially greater for minority and low income municipalities relative to the average US municipality.

We present estimates of β_i in Equation 3 in terms of standard deviation units of hurricane-strength wind speed, which is about 0.02 units of hurricane exposure. To provide some intuition on the magnitude of a 0.02 increase in our index, we plot a histogram of the index in Figure 4 and label significant storms that differ by 0.02 on our index measure. For example, Hurricane Gloria struck NYC as a Category 1 storm in 1985 with wind speeds of 78.6 kts. Within NYC and Long-Island, the storm caused $686 mn in damage. Relative to this storm, Hurricane Andrew's exposure on Lafayette, LA in 1992 comprises a standard deviation increase on the hurricane index. Lafayette experienced 93.6 kn winds due to Andrew, making it a Category 2 hurricane at that point on its path. Andrew caused $1.56 billion in damage for the entire state of Louisiana. We also present estimates of the heterogeneous treatment effects for major versus minor storms, δ_i and κ_i from Equation 4.

All fiscal outcomes are in natural logarithms so that the coefficients represent percent changes.[21] We measure outcomes in levels as well as in per capita terms in order to distinguish relative from absolute changes in local public finances. While per capita changes are informative, we focus our discussion on aggregate changes since the benefits from most public good categories studied here are unevenly distributed across the population and because several local public goods, like roadways, water infrastructure and public buildings, have large upfront costs and do not easily scale.

5.1 Effect of Hurricanes on Local Public Revenues

In our stylized model of a local government's intertemporal budget constraint in Equation 2, the change in local revenues, $\frac{dR}{dx}$, is a key parameter for predicting changes in local expenditures following a hurricane strike. We begin by estimating $\frac{dR}{dx}$ in Table 2. In Panel A, the estimates in Columns 1 through 4 show that aggregate municipal government revenues decline after exposure, with the effects concentrated in the 6–10 years after initial impact. Own-source revenues, which include all locally-generated revenues and exclude transfers, decline by around 2% for a 1 standard deviation increase in hurricane wind speed in the 6-10 years following a hurricane strike. Given the average annual own-source revenues of municipalities in our sample, this estimate implies that own-source revenues fall by \$593,520 per municipality after a hurricane. In present value terms, own-source revenues fall by over \$2.7 million per municipality in the 10-years following hurricane exposure (see Appendix Table B.1). These estimated revenue losses are approximately 40% of the revenue losses local governments faced in 2021 as a result of the coronavirus pandemic.[22]

Declines in own-source revenues are driven primarily by the shortfalls in local tax revenues.[23] Other revenues (Column 4) are not significantly affected by hurricane exposure. Panel B shows that major hurricanes induce significantly larger declines in revenues compared to minor hurricanes. The impact of a major hurricane is over four times that of a minor hurricane on total revenues (Column 1) and over twice that of a minor hurricane on own-source revenues (Column 2) in the 6-10 years after exposure.

[21] Because there are zeroes in some revenue and expenditure subcategories, we retain those municipal government observations by approximating the natural logarithm function with the inverse hyperbolic sine function: for an outcome x, $\ln(x) \approx \ln(x + \sqrt{1 + x^2})$ if x is sufficiently larger than 1.

[22] The National League of Cities projected that US cities experienced a total loss of \$134 billion in 2020, or \$6.87 million per local government (Blumberg, 2020).

[23] Appendix Table B.2 Columns 1 and 2 show the effects of hurricane exposure on municipal property taxes versus sales, income, license and other taxes not-elsewhere-classified. The estimates for these tax sub-categories are also negative, though less precisely estimated.

We estimate $\frac{dG}{dx}$ from Equation 2 in Column 5 of Panel A. Noticeably, hurricane exposure significantly increased aggregate intergovernmental transfers in the short term. This initial influx of aid appears to offset the immediate negative impacts on revenues. Most of these effects appear to be driven by federal transfers, though the effects are imprecisely estimated. Total intergovernmental transfers increase by 2.3% for a 1 SD increase in hurricane wind speed within 5 years following a hurricane strike, or about $234,563 on average. In contrast, transfers decline after the first 5 years. In Panel B, we find government transfers are approximately twice as large for major relative to minor hurricanes, although the effects are imprecisely estimated (Column 5). While data limitations preclude us from identifying the exact source of intergovernmental transfers, our findings suggest that institutions allowing for budget stabilization, like state rainy day funds, are important for mitigating local fiscal distress (Knight and Levinson, 1999).

These findings are consistent with the FEMA disaster aid response structure in the United States. Under the current system, the federal government provides crucial monetary relief shortly after a natural disaster such as debris removal, social insurance, and hazard mitigation investments. Our results mirror recent findings by del Valle et al. (2019), which finds that federal aid to Mexican municipalities exposed to major storms significantly mitigates disruptions to local economic activity at least a year following exposure. These results also echo patterns found by Deryugina (2017). Although her paper focuses on federal non-disaster aid to individuals as opposed to intergovernmental transfers studied here, Deryugina (2017) shows that an increase in non-disaster payments in the five to 10 years after a hurricane strike are instrumental in offsetting long-run declines in local wages and population. We find that a decline in transfers to local governments after five to 10 years is associated with declines in local public expenditures. Collectively, these results reveal the potentially important role of governmental transfers in smoothing individual as well as municipal spending in the aftermath of a natural disaster. The implication for policy is that intergovernmental aid may be necessary both in the short and long term to offset disruptions in local public goods provision.

5.2 Effect of Hurricanes on Local Public Expenditures

Because hurricanes have countervailing effects on local governments' revenue streams, the impact of hurricanes on local spending is theoretically ambiguous. On the one hand, we may expect some local expenditures to fall with the loss in locally-generated revenues. On the other hand, we may expect local expenditures to rise as local governments use the increased federal funds to repair and replace destroyed capital. Table 3 estimates how $\frac{dE}{dx}$ from Equation 2 is affected by these countervailing effects.

We find that hurricanes had overall negative impacts on total expenditures. Column 1 of Panel A shows that a one standard deviation increase in hurricane wind speed reduces total expenditures by 1% in the 6–10 years after the initial impact, equivalent to approximately $394,549 per municipal government per year. The expenditure decline is smaller in magnitude relative to the change in total revenues found in Table 2. The difference in the magnitudes is consistent with the inflow of short-term intergovernmental funds offsetting some of hurricanes' immediate negative fiscal impacts.

Most of this decline is concentrated in public works. Column 2 of Panel A shows that spending on public works significantly declined in the 6–10 years after exposure by 3.4%, or $435,880 per local government per year. Declines in public safety and miscellaneous spending are comparatively smaller in magnitude and imprecisely estimated.[24] Notably, public works consists of local public goods and services that are essential for low-income households, including public transportation, parks and recreation, and water and sewer services. These results suggest that hurricane exposure may be particularly damaging for lower income households reliant on these public services. As in the case of revenues, Panel B shows that major hurricanes generate significantly greater declines in expenditures relative to minor hurricanes. The average major hurricane reduces local government expenditures by 5.9% (Column 1) and public works expenditures by 13.7% (Column 2) in the 6-10 years after exposure.

In contrast to public works, government administration expenditures increased between 2.5% and 1.2% in first and second half of the post-hurricane decade, respectively (Column 5). These changes cannot be explained by increases in local employment or pay roll because we find these outcomes *decline* following hurricane exposure in Appendix Table B.2 (Columns 5 through 7). Rather, it is most likely that these administrative spending increases are a result of increased spending on disaster relief, debris removal, and use of "rainy day" funds (FEMA, 2020). Because government administration makes up a relatively small share of total expenditures (less than 5%), the magnitudes of these effects are economically small, at about $45,902 per government per year.

The present value of estimated losses in total expenditures is approximately $412,000 per municipality (see Appendix Table B.1), substantially less than total revenues losses. This is because

[24]Miscellaneous spending includes expenditures on worker compensation, insurance trusts, and interest on debt.

we estimate expenditures increase, on average, in the 1-5 years after exposure in public safety and government administrative expenses (see Table 3) following hurricane exposure. However, the present value of public works expenditure losses, the largest expenditure budget category, is over $1.4 million per municipality in the decade following hurricane exposure. For the average municipality in our sample, this accounts for approximately half their annual expenditures on infrastructure.

5.3 Local Debt & the Collateral Damage of Hurricanes

A local government's debt level and its ability to borrow are key determinants of its ability to adapt to new shocks (Adelino et al., 2017). Capital costs of long-term investments, such as infrastructure, are typically financed through debt. While the prior sections established that hurricanes decrease *current* local government resources by contracting the tax revenues and fees available for operational costs, we show in this section that hurricanes also hamper local governments' ability to finance *future* investments.

We estimate the last three terms of Equation 2 to test how hurricanes affect a local government's debt issuance ($\frac{d\Delta B}{dx}$), debt outstanding ($\frac{dB}{dx}$), and risk of default ($\frac{dr}{dx}$). Whether exposure to hurricanes leads to increased cost of capital is an empirical question that depends on how financial markets respond to updates about natural disaster risk. To estimate $\frac{dr}{dx}$, we focus on the response of ratings agencies to climate shocks in order to understand how hurricane exposure impacts perceived default risk in the primary market for municipal debt. We end this section with a discussion of potential mechanisms driving the observed decline in local capital financing.

Our analysis on municipal debt dynamics fits into a body of literature that demonstrates how natural disasters affect financial markets. Much of this prior work focuses on private sector market responses (Lamb, 1995; Cagle, 1996; Worthington and Valadkhani, 2004; Bourdeau-Brien and Kryzanowski, 2017; Krueger et al., 2020). A growing, but small body of work explores how natural disasters and climate risk affect finance in the public sector. For instance, Ouazad and Kahn (2019) shows that commercial banks offload risky mortgage assets onto government-backed banks following hurricanes. Other work on natural disasters and public finance generally focus on federal-level aggregates (Lis and Nickel, 2010; Noy and Nualsri, 2011; Melecky and Raddatz, 2011). Ouattara and Strobl (2013) provide the closest parallel to our study, as they explore how hurricanes impact federal government spending, debt, and tax revenues within the Caribbean.

We, first, assess how hurricanes impact local government borrowing costs by focusing on municipal bond ratings. We use a novel dataset on bond ratings from Moody's Analytics. These data provide the rater's assessment of risk on over 600,000 municipal debt instruments dating back to the 1930s, though data prior to 1970 are sparse. Moody's data cover issuance activities for approximately 29% of all municipal issuers in the US.[25] Bond ratings are an important signal of an issuer's borrowing costs; the cost of issuing debt increases as the risk of default increases, and bond ratings measure this risk (Capeci, 1991).[26]

We create a municipality-year-level bond rating from Moody's instrument-level ratings data by calculating the weighted average rating across all instruments issued by a given municipality and rated in a given year, where the weight is the size of the instrument sale. While the Moody's ratings data reflect the primary market (or new issuance events) Moody's updates their ratings of issuance events over time. This means that we can observe changes in the rating of the same debt instrument over time. We explore how hurricane exposure impacts, both, the composition of debt instruments and the ratings of particular debt instruments in our analysis.

Recent work on sea level rise by Painter (2020), Goldsmith-Pinkham et al. (2021), and earthquake risk by Fowles et al. (2009) are relevant to our analysis of municipal borrowing costs. These papers utilize information shocks to show that municipal bond markets capitalize natural disaster risk. Our study complements this prior work in two ways. First, we combine bond ratings data with data on local public finances to show that climate shocks reduce debt utilization through ratings agencies like Moody's. This channel is important to document because debt default risk —which Moody's ratings measure—accounts for over 74% of the price of municipal bonds, and is thus an important factor to consider for policy makers aiming to reduce local government investment costs (Schwert, 2017).[27] Second, our approach informs how the municipal bond market reacts to a type of natural disaster *shock* as opposed to anticipated sea level rise or earthquake risk.

Default risk, along with the risk-free rate, liquidity risk, and maturity risk are all components of an issuer's borrowing cost, or their bond yield (Brigham and Daves, 2015). Among these four

[25] Moody's provides rating services for 14,438 municipal issuers from 1972 through 2017, whereas approximately 50,000 such entities exist in the United States (MSRB 2019). Standard & Poor's and Fitch dominate the other two-thirds of the bond rating market.

[26] Hubler et al. (2019) discusses how variation in agencies' risk assessments have significant impacts on borrowing rates for corporations as well as municipalities. While credit rating agencies faced substantial scrutiny following the 2007 market crash for biased and subjective rating practices, particularly for mortgage-backed securities, ratings agencies like Moody's remain an integral role in financial markets because creditors rely on their publicly-available ratings in order to make investment decisions (Hubler et al., 2019; Cornaggia et al., 2018).

[27] Default risk factors into the investment premium for municipal debt to a much greater degree than corporate debt. Driessen (2005) finds that default risk accounts for less than 31% of the premium for corporate bonds.

components of the bond yield, bond ratings specifically measure the probability of default. We translate Moody's bond ratings into probabilities of default using Standard & Poor's Global Ratings US Public Finance Default Study (Witte and Gurwitz, 2018). While we are unable to observe bond yields directly, we include controls for bond attributes that influence the liquidity risk and maturity risk, including: the coupon rate, the share of bonds sold at public auction, the share of bonds that are general obligation versus revenue-backed, years to maturity, the size of the bond, and the baseline population size of the issuer. Year fixed effects account for variation in the risk free rate. We include these controls in all specifications in order to create an "apples to apples" comparison across debt instruments, as well as to absorb all variation in the effective bond yield aside from the bond rating, itself. In a robustness check in Section 7, we conduct analysis using bond instrument fixed effects in order to account for potential compositional changes in debt instruments over time and our conclusions do not change.

The first four columns of Table 4 show the evolution of credit risk in the 10 years following hurricane exposure. We focus on four measures of municipal governments' credit risk: the 10-year municipal bond default risk, and the share of municipal bonds that are low risk (above "Baa"), medium risk (rated "Baa"), and high risk (ratings lower than "Baa"). Our results suggest that hurricane exposure significantly increases municipal bond default risk. A one standard deviation increase in hurricane wind speed raises the 10-year default risk by 0.1 percentage points (Panel A, Column 1), equivalent to a 13% increase in the five years after hurricane exposure based on our sample standard deviation of the 10-year default risk (0.76 percentage points).[28] This effect persists in the 6-10 years after a hurricane.

When considering the magnitude of this change in default risk, it is important to consider that municipal bond ratings change minimally on average. Approximately 90% of municipal bond ratings remain unchanged over a two-year period (Holian and Joffe, 2013). Furthermore, ratings agencies assess bond risk only for municipalities that pay them to do so. In their literature review on the determinants of municipal bond default, Holian and Joffe (2013) find that cities that choose to be rated are more likely to have a lower default risk than cities that do not choose to be rated. Municipalities in the Moody's data have significantly larger populations, lower poverty rates, and greater annual revenues, expenditures, and debt obligations relative to our full-sample

[28] In our sample, the mean 10-year default risk is about 0.3%, whereas the median is about three times smaller, or 0.1%. Given that distribution of bond defaults is highly skewed, using sample mean as the base for comparison can overstate the estimated impacts.

of municipalities. This implies that hurricanes likely increase the 10-year default risk of un-rated municipal debt more than 0.1 percentage points documented here.[29]

The hurricane-induced change in municipal default risk changes the overall composition of risk for a municipality's bond portfolio. Table 4, shows that the share of medium and high risk bonds (those rated "Baa" and below, respectively) increases significantly in the decade following a hurricane. A one standard deviation increase in hurricane wind speed increases the share of bonds that are medium risk by 5.2 percentage points (Panel A, Column 3), equivalent to a 1.4% increase based on the sample standard deviation of the outcome. Similarly, the share of bonds that are high risk increases by 1.4 to 1.7 percentage points (Panel A, Column 4), which is translates to 10–12% increases in the share of high risk bonds relative to the sample standard deviation. Panel B decomposes the average effects of the hurricane exposure index into indicators for whether a local government ever experiences a major (wind speed exceeds 96 knots) or minor hurricane (wind speed is between 64 and 96 knots). Major hurricanes appear to drive most of the increase in default risk of a municipality's bond portfolio. Notably, minor storms appear to have the opposite effect on default risk as major storms, although the effects are less precisely estimated and are smaller in magnitude. This may be a result of the fact that populations do not change significantly in the immediate aftermath of minor storms (a pattern we clarify in the following section) and that intergovernmental transfers increase in the 1-5 years after storm exposure.

We take advantage of the bond data frequency to estimate default risk dynamics in the years leading up to and following hurricane exposure. Figure 5 presents the dynamic effect results. In particular, we estimate

$$y_{ist} = \sum_{k=-10}^{10} \beta_k H_{it+k} + \alpha_i + \alpha_{st} + \delta'(\mathbf{X}_i \alpha_t) + \varepsilon_{ist}, \tag{5}$$

where H_{it+k} is an index for hurricane exposure for municipality i in k years since year t when we observe outcome y. For example, if $t = 2007$ and $k = 2$, then the coefficient on H_{is2009} measures how an outcome in 2007 (y_{is2007}) is associated with hurricane exposure from 2009. Conversely, if $t = 2007$ and $k = -2$, then the coefficient on H_{is2005} relates an outcome in 2007 to hurricane exposure from two years prior in 2005. In the absence of omitted trends or confounding shocks,

[29] As a robustness check in Appendix Table B.10 we estimate revenue and expenditure outcomes using only the 581 municipalities that match to the Moody's data and find very similar results. Our results are also robust to excluding years after the 2007 market collapse, when municipalities were more likely to "shop" across agencies for higher ratings (Sangiorgi et al., 2009; Farmer, 2015). Finally, our bond ratings results are robust to using only a balanced panel of 88 municipalities from 1982 through 2017, suggesting that attrition or selection into the Moody's dataset are not driving our conclusions. These results are available upon request.

current municipal debt outcomes are unlikely to predict *future* hurricane exposure. Therefore, this exercise serves as both a robustness check on potential spurious spatial correlations between hurricane exposure and municipal debt ratings (Kelly, 2019) and allows for easy visualization of hurricane exposure's effects over time. To increase power, we create 2-year bins (with the exception of $k = 0$) so that, for example, H_{it+2} measures impacts in year t of exposure from 1 and 2 years prior to year t. Because hurricane data are only available up to 2019, our analysis of municipal bond dynamics cover years between 1982 and 2009, or up to 10 years prior to the last year of hurricane exposure in our sample.

Figure 5 corroborates our average effect findings: hurricane exposure increases municipal default risk as perceived by ratings agencies, leading to a shift in the average risk profile of a municipality's debt portfolio from lower to higher risk bonds. Notably, we do not find significant pre-event trends in any of these figures, suggesting that post-hurricane changes are a direct result of the hurricane as opposed to pre-existing differences in default risk among hurricane-exposed municipalities. These results imply that municipalities face interest rates on debt that are approximately 1% larger after exposure to a hurricane.[30] For a city like Philadelphia, which had 84 ongoing road and bridge projects as of 2020, a 1% higher interest rate means that the city would face $13 million in added infrastructure costs for that year's projects after exposure to a hurricane.[31]

Whether changes in default risk translate into more expensive debt (higher bond yields) relies on the assumption that credit markets accurately reflect all available information and operate efficiently. Thus, it is an empirical question whether greater default risk impacts municipal use of debt. To understand this, we next explore how hurricanes impact municipal debt. We employ only the subset of cities that were available in the Moody's data in order to interpret debt results relative to our bond ratings results. This subset of cities is generally larger in population than the average city in the Census of Governments.[32] Columns 5 through 7 in Table 4 show estimates

[30] We arrive at this estimate using a back-of-envelop calculation as follows: we translate the 0.1 percentage point change in the 10-year default risk following exposure (Table 4) to the corresponding change in bond ratings using Standard & Poor's Global Ratings US Public Finance Default Study (Witte and Gurwitz, 2018). Their study shows that bonds rated "AAA" (or "Aaa" on the Moody's scale) have a default risk of zero for 10-year debt instruments; whereas bonds rated "A" (or "A2" on Moody's scale) have a default risk of 0.11 for 10-year debt instruments. Next, we use the Federal Reserve Bank's Pricing Index associated with the Municipal Liquidity Facility (Federal Reserve Board, 2020) to compare the interest rates charged for "AAA" relative to "A" rated bonds; this difference is 100 basis points, or 1%.

[31] Based on an estimated total cost of $1.33 billion for 56 total road and bridge projects under construction and 28 planned for FY 2020 (Riley, 2020).

[32] As a robustness check in Section 7, we estimate our revenue and expenditure results using only the Moody's sample of cities and find very similar results (shown in Panel E of Appendix Table B.10).

of how local government debt responds to hurricane exposure.[33] Our debt outcomes include total debt outstanding, long-term debt issued, and retired long-term debt. While average effects of hurricane exposure shown in Panel A indicate imprecise, negative impacts of hurricanes on debt, Panel B Column 5 shows that major hurricanes significantly reduce total debt outstanding in the 10 years following hurricane exposure. It is difficult to conclude whether this reduction is driven by decreased issuance of new debt or increased retirement of existing debt, though the sign of the coefficients in Columns 6 and 7 implies both effects may be happening in the 6-10 years after a major hurricane. We caution against drawing strong conclusions from Panel B results with debt issuance and debt retirement as outcomes because the Census of Governments quinquennial data structure likely omits several instances of issuance or retirement. Results from total debt outstanding are more precisely estimated because this is a stock variable, as opposed to issuance and retirement which are flow variables. Column 5 in Panel B implies that exposure to a major hurricane reduces debt outstanding significantly by 19.2% in the first five years and 25.9% in the next 6-10 years following hurricane exposure.

5.4 Mechanisms Driving Declines in Bond Ratings

Our analysis provides new evidence that hurricane exposure depletes local public financial resources, reduces public goods expenditures, increases default risk, and reduces debt utilization. These results indicate that climate-related natural disasters impose costs on local governments that can propagate in the long run through delayed capital investments and depleted debt reserves. Less clear, however, is the mechanism that drives changes in municipal default risk and subsequent changes in debt. Ratings agencies may consider a government inherently more at risk to natural disasters if those disasters become more salient. Given few municipalities disclose climate-related risk when issuing debt (Bolstad et al., 2020), the salience of such events likely has greater impact on ratings than a de facto measure of climate risk.[34] On the other hand, natural disasters can impact local public finance through raising out-migration, changing the demographic composition of the incumbent population, reducing house prices, or depressing local economic activity. Ratings agencies consider these fundamentals when assessing municipal default risk (Rubinfeld, 1973; Kliger and Sarig, 2000). Consequently, it is possible that hurricanes impact debt ratings indirectly through their effects on population and local economic activity. Understanding whether ratings agencies respond to such

[33] The debt outcomes for fiscal year 2017 are not yet available in the Census of Governments, so we report the estimates for 1982–2012.

[34] Goldsmith-Pinkham et al. (2021) finds, for instance, that the municipal bond market capitalizes climate change risk from sea level rise only after the IPCC 2013 report.

routine fundamentals as opposed to hurricane exposure, itself, is important for projecting the future costs of hurricanes.

To this end, we first assess how hurricanes impact local economic activity by focusing on changes to local population, employment, home values, and demographics. We, then, explore whether ratings agencies adjust their assessment of risk by comparing municipalities that miss exposure to hurricane-strength winds relative to bordering towns that are hit. From the perspective of Moody's, these two types of locations shared similar ex ante exposure risk and should experience similar ratings downgrades if ex ante risk to climate shocks matters for default risk.

Declining Local Economic Conditions?

Table 5 reports how hurricane exposure impacts local economic activity. We aggregate analysis for some outcomes in Table 5 to the county-level in order to obtain annual variation in outcomes rather than relying on municipal-level from the US Census which vary only by decade. We source county-level data on population and employment from the BEA, as well as county-level home values from Zillow. Overall, we find that population decreased significantly throughout the decade after a hurricane strike, particularly after major hurricanes strikes. A one standard deviation increase in hurricane wind speed reduces population by approximately 0.7% in the 6-10 years following exposure (Panel A, Column 1). Columns 2 through 4 show county-level outcomes from the BEA. The difference between population estimates at the municipal-level in Column 1 versus the county-level in Column 2 may be driven by individuals relocating between municipalities within the same county following a hurricane strike. If two municipalities serve as close substitutes, individuals may re-optimize and choose a location with lower perceived hurricane exposure risk. Such re-optimization is less likely, however, for households facing high mobility costs.

In Column 3, we find county employment estimates that mirror the population estimates in the previous two columns. Employment falls by 0.5% for a standard deviation increase in hurricane wind speed and over 4% following major storms. These employment effects echo prior findings by Belasen and Polachek (2009), who find major storms decrease county employment by 4.7% on average. In the last column, we find that home values decline immediately following hurricane exposure, as well as in the 6-10 years after exposure, corroborating prior work by Hallstrom and Smith (2005); Davlasheridze et al. (2017); Ortega and Taṣpinar (2018); Muller and Hopkins (2019) and Boustan et al. (2020). We interpret these results with caution, however, because we find evidence of level differences in prices across exposed versus non-exposed municipalities prior to hurricane exposure in Figure 6.

In Panels C and D of Table 5, we test whether hurricane exposure causes local populations to become lower income or more likely to require public assistance. We aggregate the treatment effect into an average decadal effect because the outcomes in Panels C and D are sourced from the US decennial census. The poverty rate increases by 0.1 percentage point (a 1% increase based on the sample mean) in the ten years after hurricane exposure for every standard deviation increase in wind speed. The unemployment rate similarly increases by 0.2 percentage points (a 3% increase based on the sample mean). Major storms have the largest impact on these outcomes. The poverty rate increases 1.5 percentage points following a major storm. As a comparison, the US poverty rate increased one percentage point between September 2020 and September 2021 during the COVID-19 pandemic (Delavega, 2021). In general, these findings show that hurricane exposure depresses local economic activity for at least a decade following exposure.

We test for evidence of pre-trends and dynamic effects utilizing the annual variation available in the county-level data in Figure 6. For exposition purposes, we normalize the partial effect coefficients by the "Year -2" coefficient. Panel A shows a clear trend break in population following hurricane exposure. Panel B shows that employment falls below that of non-exposed county levels in the years following hurricane exposure, although the trend break is less pronounced. These annual-level partial effect estimates do not exhibit significant pre-hurricane trends, suggesting that omitted trends related to population or employment are unlikely to be driving our local public finance results. Panel C shows that home values fluctuate before hurricane strikes. There is a short-term increase in home prices, possibly due to supply constraints, however prices begin to fall by year four.

Collectively, the evidence is consistent with the hypothesis that ratings agencies downgrade municipal bond ratings due to economic decline and destabilization of the local tax base. A competing hypothesis is that ratings agencies downgrade bond ratings following hurricane exposure due to changes in their perceptions of local governments' ex ante risk. We examine these alternative explanations below.

Changes in Moodys' Climate Risk Assessment?

We explore whether ratings agencies update their risk assessment procedures in the aftermath of hurricane shocks. Our approach compares changes in bond ratings across municipalities exposed to a major hurricane relative to municipalities in adjacent counties that missed exposure to the same storm's major hurricane-strength winds by chance. This sub-sample consists of 919 municipality-year observations. Figure 7 plots coefficient estimates from this "neighboring municipality" analysis side-by-side with coefficient estimates from our main debt results in Table 4. The "neighboring municipality" estimates in Figure 7, denoted by diamonds, are based on the same estimation equation from Equation 3 except that we replace municipality-specific fixed effects with *municipality group*-fixed effects.[35] For ease of exposition, we plot only estimates of the impact of a 1 standard deviation change in hurricane wind speed in the 6-10 years after exposure.[36] We posit that estimates showing no differences in the exposed municipality relative to a neighboring, *nearly* exposed municipality imply that Moody's assesses the risk of the exposed municipality equally to that of the municipality that nearly missed exposure to major hurricane-strength winds.

Instead, results of Figure 7 mimic results of our main approach in Table 4. Exposed municipalities experience an increase in their average debt instrument's risk of default and an increase in the share of bonds rated as medium or high risk relative to municipalities not directly exposed to major hurricane-strength winds. This suggests Moody's does not update bond ratings using changes in ex ante risk perceptions. A caveat to this interpretation is that positive spillovers will mask downgrades in bond ratings in our empirical design. For instance, if population and business activity leave the location struck by major winds and enter into the neighboring municipality, any downgrades in bond ratings from ex ante risk will be offset by increases in ratings due to improvements in local economic conditions. Given the magnitudes of estimates from the "neighboring municipality" analysis are very similar to our main analysis, we conclude that ex ante climate risk is not the main factor ratings agencies consider when determining municipal bond default risk. Rather, the post-hurricane increases in bond default risk that we observe in Section 5.3 are primarily a result of local tax revenue losses and local economic shocks.

Findings by Goldsmith-Pinkham et al. (2021) and Painter (2020) show that investors do

[35]To construct municipality groups, we first identify the list of municipalities that have ever experienced wind speeds at least 96 kts. For each municipality on this list, we create a unique municipality group based on the set of counties that are adjacent to the hit municipality. If an adjacent county appears in multiple municipality groups, we use the largest union of these groups. In unreported results, we control for municipality fixed effects and replace state-by-year fixed effects with municipality group-by-year fixed effects. The results from these regressions are similar to what we report in Appendix Table B.3 and are available upon request.

[36]We report the "neighboring municipality" estimates of the 1-5 year average effect, and effects by storm intensity in tabular form in Appendix Table B.3. Generally, the 1-5 year effects are similar to the 6-10 year effects but smaller in magnitude.

capitalize risk from sea level rise in the secondary market for municipal bonds. Though outside the scope of this paper, it is possible that investors in the secondary market respond similarly to hurricane shocks and actively factor in climate-specific risk when making bond purchase decisions. Our results suggest that in the primary market, climate-specific risk does not impact bond default risk assessment differently than other non-climate related shocks.

5.5 Effect of Hurricanes on Per Capita Local Public Finances

Our analysis thus far demonstrates that hurricanes cause declines in local aggregate public revenues and local public expenditures. We also find that municipalities shrink in population. Consequently, it is unclear whether per person service provision changes after hurricane exposure. In Table 6 we explore how hurricane exposure impacts per capita revenues, expenditures, and debt. We see some similar patterns to the aggregate outcomes: own-source revenues fall by 1.3% and public works expenditures decline 2.6% in the 6 to 10 years after exposure, the period after intergovernmental transfers dissipate. Like the aggregate results, per capita government administrative expenditures increase between 2-3% in the decade following exposure. Long-term debt issuance per capita declines as well, though the estimates are net precisely measured.

There are notable differences between the per capita and aggregate results, however. Total revenues and total expenditures per capita do not significantly change in the 6-10 years after exposure, and, in fact, some expenditures per capita increase in the immediate aftermath of hurricane exposure. Specifically, per capita expenditures in public safety increase by 1.6% in the 1-5 years after hurricane exposure. These changes likely reflect greater per-person needs for emergency interventions provided by fire and police departments following a hurricane strike.[37]

These results imply that residents who remain after a hurricane strike may not experience any changes in the quality or quantity of public goods and services, despite the fact that total government budgets shrink. It is outside the scope of this study to investigate whether quality measures of public services, like test scores, crime rates, or operating efficiency change in the aftermath of hurricanes. However, two pieces of evidence suggest that the quality of some services may be declining for incumbent populations. First, the decline in public works expenditures per capita in the 6-10 years after exposure indicates that goods with larger fixed costs - like sanitation,

[37] A FEMA 2008 report highlighted the need for local fire departments to plan for emergency responses to natural disasters, including hurricanes: "Disaster and major incidents demand effective coordination among fire and police personnel. Traffic control, curfews, and limits on access to damaged areas all affect fire department operations and require close cooperation with law enforcement (Strambaugh and Sensenig, 2008)."

sewerage, utilities, roads and mass transit - become harder to provide. Second, (as discussed previously in Section 5.4) we find evidence that higher income individuals are more likely to leave in the aftermath of a hurricane, leaving an incumbent population with a marginally higher poverty rate and a higher unemployment rate. To the degree that the lower-income incumbent population require more services and assistance from their local governments, a null effect of hurricanes on per capita revenues & expenditures may be suggestive of worsening public services.

Whether or not services become lower quality, our per capita results show that hurricane exposure increases the need for intergovernmental transfers. This echoes prior work by Deryugina (2017). In the absence of such transfers, it is possible that the quantity and quality of goods and services may decline following hurricane exposure.

One caveat to these conclusions is that per capita values are likely to be measured with error. Local government population data are sourced from the Census Bureau's annual population estimates, which use data on births, deaths, and migration to infer changes to the local population. Unlike the fiscal measures, the population data are not supplied directly to the Census of Governments by local governments. Thus, estimates reported in Table 6 may be more susceptible to Type II measurement error compared to estimates from aggregated outcomes in Tables 2, 3 and 4.

6 The Unequal Impacts of Hurricanes

Previous literature shows that places with high concentrations of minorities and low-income households are on average, disproportionately affected by negative environmental hazards (Brooks and Sethi, 1997; Hanna, 2007; Mohai et al., 2009; Banzhaf et al., 2019). The literature has substantially less to report about demographic differences in hurricane exposure. Recent work by Bakkensen and Ma (2020) shows that low income and minority households are more likely to sort into high-risk flood zones because high income households outbid them for properties in low-risk areas. Ratnadiwakara and Venugopal (2020) show evidence of home price reductions after major flood disasters lead to an adverse selection of less wealthy homebuyers, who are also more likely to default on their mortgages.

We test whether local governments of minority and low-income groups are more adversely impacted by hurricane shocks. We focus on three municipality attributes: share of population below the poverty line, share of population that are non-white, and share of population with less than a high school degree. Our motivation for focusing on these three sources of heterogeneity stems from the two key facts. First, our descriptive statistics in Table 1 show that municipalities exposed to hurricanes had seven percentage points larger populations of non-white residents as of 1970 compared to municipalities that never experienced a hurricane between 1972 and 2017. Second, lower income and lower educated individuals may face larger barriers to relocating to avoid environmental hazards or negative local shocks due to credit constraints, access to public assistance, or discrimination (Banzhaf and Walsh, 2008; Gallagher and Hartley, 2017; Lin, 2019; Notowidigdo, 2020; Christensen and Timmins, 2021).

To carry out this heterogeneity analysis, we interact the hurricane exposure measure in Equation 3 with baseline municipality demographic characteristics measured as of 1970. We focus on baseline attributes because demographic composition of municipalities may change as a consequence of hurricane exposure. To aid the interpretation of the coefficients, we demean the demographic attributes and report the heterogeneous effects in terms of a 1 standard deviation increase in the attributes. For ease of exposition, we also combine the 1-to-5-year effect (β_1) and 6-to-10-year effect (β_2) into one parameter that measures the hurricane's effect averaged over 10 years following exposure.

Our findings in Figure 8 show that cities with a higher 1970 share of residents below the poverty line, non-white residents, and residents with no high school degree are significantly more harmed by hurricanes. The first row of each panel shows the main effects; the second row shows the heterogeneous treatment effects.[38] The coefficient estimate on revenues indicates that municipalities with a 1 standard deviation greater share of residents in poverty, that are non-white, or have less than a high school education experience, respectively, 1.3%, 1.3%, and 0.8% additional declines in own-source revenues as a result of a one standard deviation increase in hurricane wind speed. Compared to hurricanes' main effects, the magnitudes of our estimates imply 1.5 to 2.6 times larger declines for these low socio-economic status (SES) municipalities. Expenditures also fall more in these low SES municipalities, though the effect is precisely estimated only for historically non-white municipalities. The 10-year default risk increases by 0.1 percentage points for communities with higher shares of low-SES demographics, but does not change, significantly for communities with average demographic characteristics. Lastly, population declines also appear larger in low-SES municipalities, though most of the estimates are less precise.

Overall, the results demonstrate how hurricanes can cause a divergence in fiscal outcomes

[38]We report coefficient estimates of Figure 8 in tabular form in Appendix Table B.4.

across municipalities that differ demographically, even within the same state. This suggest that the spatial distribution of hurricane risk can contribute to existing spatial inequality in the US (Chetty et al., 2014).

7 Robustness Tests

Through a series of robustness checks, we show that our results are largely unchanged by: alternative specifications; controlling for possible pretrends; sampling selection of decades, hurricanes, or municipalities; alternative measures of hurricane exposure; or the level of government aggregation.

Assessing Pre-trends—Our empirical approach requires that hurricane and non-hurricane municipalities exhibit similar potential outcomes in the absence of hurricane exposure. While our pre-trend analyses in Figures 5 and 6 provide empirical support for the parallel potential outcomes assumption with respect to bond ratings and municipality characteristics, data constraints preclude us from conducting similar analyses for the fiscal outcomes because Census of Governments data are only observed once every five years. As an alternative, we test whether hurricane exposure 5 and 10 years in the future have any effect on current municipal revenues, expenditures, debt, and default risk. Appendix Tables B.5 through B.8 show these results in the last two rows of each table. The "lead" coefficients of hurricane exposure in the *next* 0-4 years and 0-9 years are close to null and are rarely statistically significant. Appendix Table B.6 reports public expenditures in the 0-9 years before exposure are significantly lower relative to the year of initial exposure, suggesting a possible pre-trend. To further investigate, we show results of our main parameters of interest from a specification with municipality-specific linear time trends in column (4) of each table. The time trends absorb differences across local governments in linear growth paths. The magnitudes are very similar to our baseline estimates, although the standard errors are larger. In general, these results support our premise that hurricane exposure is conditionally random and our estimates are not driven by differences in fiscal growth prior to exposure across hurricane and non-hurricane municipalities.

Sensitivity to Hurricane Exposure Measure—Our preferred measure of hurricane exposure can be interpreted as capturing the impact of the most severe storm a local jurisdiction experiences in a give time period. This choice of measurement is motivated by the evidence that storms' damages are a result of storm severity as opposed to storm frequency (Boustan et al., 2020; Emanuel, 2011). In Appendix Table B.9, we show that our results are largely unchanged using alternative measurements of hurricane exposure. For example, when we use linear wind speeds or squared wind speeds to calculate hurricane exposure, we find similar magnitudes as using cubed wind speeds. We also find similar estimates if we do not impose zero damages for wind speeds below 50 knots (column 4) or if we exclude major hurricanes from 2005 (Katrina, Rita, and Wilma), which was a year that saw unusual hurricane activity (column 5). Results differ under a specification where we use a binary indicator for hurricane exposure in column (6). The binary indicator masks heterogeneity across hurricane intensity, thus estimates are generally attenuated and imprecisely estimated.

Another concern is that our difference-in-differences estimates may be biased if treatment effects are heterogeneous over time or across cohorts, as highlighted in recent work on two-way fixed effect (TWFE) estimators (Borusyak et al., 2020; De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2020; Goodman-Bacon, 2021). For instance, our empirical design uses municipalities that were previously exposed as well as municipalities that were never exposed during the study period as controls for treated municipalities. If hurricane exposure has lasting effects that persist beyond a decade or more, then our previously-exposed control group does not provide a valid counterfactual. We try to mitigate potential bias resulting from persistent effects by using only the first time a municipality is exposed to hurricane-strength winds between 1982 and 2007 as our measure of hurricane exposure in Column (7). This specification also controls for hurricane exposure from 1972-1981 in order to account for persistent effects at least 20 years prior to measuring an outcome. Because the sample is heavily restricted in this specification (outcomes are measured only from 1992 through 2017), we lose some precision and effects are attenuated. However, we still see evidence that revenues and expenditures decline; and default risk increases in the decade following hurricane exposure.[39,40]

Sensitivity to Empirical Specification & Sampling—We test whether our conclusions are sensitive to alternate empirical specifications or the sampled time period, hurricanes, or local governments in Appendix Table B.10. In Panel A, we do not weight observations by the 1970 municipal population and find results qualitatively similar to those in Tables 2 and 3, although the effects are imprecisely estimated. This imprecision reflects the fact that annual changes to budgetary items are

[39] A related benefit of this specification is that it relies on a balanced panel of hurricanes to identify the 1-5 and 6-10 year effects. Consequently, the same hurricane events identify the 1-5 and 6-10 year effects for a particular municipality.

[40] In unreported results, we apply a generalized TWFE estimator from Borusyak et al. (2020). This estimator allows for arbitrary heterogeneity and dynamics of causal effects of a binary treatment. Because the estimator requires a binary treatment effect, we specified the treatment to be the first exposure to a major hurricane between 1982 and 2007. This estimation procedure was quite data-intensive and substantially restricts the number of observations, as it used only municipalities never exposed to a hurricane as controls. While most of our point estimates were a similar magnitude to our main results, the standard errors were very large, in for some outcomes, could not be calculated due to a small sample size.

more accurately tracked for large local governments compared to smaller local governments within the Census of Governments database. Our main specification weights by population in order to reduce this source of measurement error.

We next, assess sensitivity to the our selected sample. Hurricanes are more likely to strike larger cities mechanically (larger land area), and because larger cities tend to locate along coastlines closer to the path of hurricanes. While we believe the parallel trends assumption holds in our case, it is possible that our results have limited external validity if the non-hurricane municipalities in our sample are poor representatives of average non-hurricane municipalities within Atlantic states. We test the robustness of our results to sample selection in two ways. First, we employ a propensity score matching approach. We assign each hurricane municipality to a non-hurricane municipality based on a propensity score using one-to-one nearest neighbor matching. The propensity score is a function of 1970 demographics (population, average educational attainment, nonwhite population and poverty rate) and geographic characteristics (land area and distance to coastline). This process excludes 3,207 non-hurricane municipalities leaving 756 to serve as controls for the 2,181 hurricane municipalities. We, then, re-estimate Eq. 3 with matched-group fixed effects rather than municipal government fixed effects and inverse weight observations based on the similarity of propensity scores within matched pairs.[41] Appendix Table B.11 shows very similar results to our main findings, often with larger magnitudes. Estimated effects on default risk and bond composition are notably smaller and noisier than those found with a larger sample size in Table 4. However, the overall pattern is similar: default risk marginally increases and ratings agencies rate municipal debt as higher risk following hurricane exposure.

In our second approach, we exclude very small municipalities that are likely to be poor counterfactuals to hurricane-exposed municipalities. Panels B and C of Appendix Table B.10 show, respectively, that restricting our sample to only municipalities with non-missing 1970 covariates and using the full sample of municipal governments, as opposed to a balanced panel, render similar conclusions to our main results. Panel D, further, shows that our results are robust to excluding very small municipalities with populations below the 5th percentile.

Finally, we test whether the revenue and expenditure results are robust to using only the 581 municipalities that match to the Moody's data. Panel E of Appendix Table B.10 provides very similar conclusions: hurricane-strength winds reduce total revenues by nearly 2% and to-

[41] We weight by the inverse difference in propensity scores because of somewhat limited common support across matched treated and control units. Details of the propensity score distributions are available upon request.

tal expenditures by 1.4% in the 6-10 years after exposure. These declines appear to occur after intergovernmental transfers subside.

Sensitivity to Alternative Treatment Units—We assess whether our results are sensitive to using alternative government treatment units. This robustness check serves two purposes: first, to test whether our focus on municipal governments is externally valid for other local government types like townships; and second, to explore the incidence of public finance costs in the face of hurricanes.

Our preferred empirical approach focuses on municipal governments because municipalities are the most common general purpose government type and because they perform similar roles across US regions.[42] In contrast, county governments, special districts, and townships can differ significantly in their provision of goods and services from one region to another. In Appendix Table B.12 Panel A, we nonetheless include all local government types in our analysis, including other general-purpose and special-purpose governments. We aggregate outcomes across local governments to the county level, and replace municipality fixed effects with fixed effects for the local government type. In Panel A, we also interact government type with state-by-year fixed effects and baseline covariates to allow local government outcomes to trend differently across government types and states. Regressions are weighted by 1970 county population.[43] Although differences in sample compositions, geographic units, and estimation methods render direct comparison with earlier results in Table 2 and Table 3 difficult, results are, nevertheless, qualitatively similar after including all local government types in the analysis. The negative short-term effects of hurricanes on revenues and total expenditures are larger in magnitude than our main estimates suggest. The longer-term 6-10 year effects are similar in magnitude to our main results, though less precisely estimated.

In Panels B and C of Appendix Table B.12, we explore how results differ when considering the impact of hurricanes at the county geographic unit level (the smallest geography for which geographic identifiers are available for all government types) and at the state government level, respectively.[44] In Panel B, we also find evidence of revenue and expenditure declines among

[42] Municipalities account for over 22% of all government types in the Census of Governments, whereas county governments account for 6% and townships account for 16%. Special districts, school districts, and state governments make up the remaining share.

[43] Because special-district governments have been increasing sharply over time, instead of creating a balanced sample of local governments, we use the full sample of governments for this analysis. For instance, while the number of local government-year observations has remained relatively stable for other government types, the number for special-district governments increased from 6,637 in 1982 to 10,989 in 2017 in our sample.

[44] Regressions in Panel B are weighted by 1970 county population. In Panel C, we interact baseline state-level covariates with linear time trends and cluster standard errors at the state level.

hurricane-exposed counties, though smaller than the magnitudes in Panel A for local governments. This indicates intergovernmental transfers likely occur between local governments within the same county following hurricane exposure. At the state level, we observe no significant revenue changes, though intergovernmental transfers and public works expenditures increase.[45] Taken together, Appendix Table B.12 suggests that the fiscal impacts of hurricanes diminish as higher levels of government. These findings support prior work by Strobl (2010) and underscore how fiscal costs of hurricanes estimated from state or federal aggregates will likely understate the realized costs.

Sensitivity to Debt Instrument Attributes—Our analysis of debt dynamics focuses on variation in the 10-year default rate, a commonly-used long horizon benchmark. However, ratings agencies may respond to hurricane shocks differently for short-term relative to long-term debt instruments. Appendix Table B.13 shows that the risk of default does not change for short-term debt instruments maturing in 1 or 5 years (Columns 1 and 2); but debt instruments that mature in 22 years have a similar increase in default risk as the 10-year debt instruments (Column 3). In Columns 4 through 7, we estimate Equation 3 at the debt instrument level rather than the municipal level. This allows estimated hurricane effects on bond ratings to differ across debt instruments with differing characteristics such as the coupon rate, whether the instrument is a general or revenue-backed bond, and the maturity length. These specifications also weight by the bond's initial sales amount. Even allowing for this added flexibility, our results are very similar to those shown in Table 4: hurricanes increase the composition of municipal debt categorized as medium and high-risk by approximately 5pp and 1pp, respectively in the 6-10 years after exposure.

8 Conclusion

We examine the impact of hurricanes on local governments through their effects on the provision of local public goods and resources. Our results show that hurricanes cause locally-generated revenues as well as expenditures to fall significantly. In the decade following major hurricanes, local revenue sources and expenditures fall between 5 and 6%. Local governments with large minority, low income, or low educated populations face the largest revenue and expenditure cut backs following hurricanes. Intergovernmental transfers to local governments offset some of the

[45] We also collect data on states' budget stabilization funds, i.e., "rainy day funds," from the National Association of State Budget Officers, which provide fiscal surveys of states. In unreported results, we find that the effect of hurricanes on these funds is large and negative, especially in the immediate aftermath. We estimate that the funds decrease by 57% ($p < 0.01$) in the 1–5 years post hurricanes for a one standard deviation increase in hurricane winds. The magnitude of this effect reduces by one-fifth in the next 6–10 years and becomes statistically indistinguishable from zero.

initial fiscal impacts of hurricanes, but do not, on average, alleviate declines in local government funding sources within the decade following exposure. In contrast, hurricanes do not significantly decrease total revenues or expenditures per capita because per capita governmental transfers and expenditures on emergency aid increase significantly. Minimal changes in per capita expenditure totals is potentially problematic given that we find local populations become more impoverished with higher unemployment rates following a hurricane.

Our paper provides evidence that natural disasters can exacerbate budgetary pressure for local governments by increasing their borrowing costs, depleting the tax base, and inhibiting their ability to make large, capital investments. In so doing, climate-induced natural disasters can discourage local governments from investing in precisely the hazard mitigation technologies or reconstruction projects required to deflect future damages from hurricane shocks.

The negative fiscal effects from major hurricanes documented here stand in contrast with research on the medium term effects of war time military bombings (Miguel and Roland, 2011; Brakman et al., 2004; Bosker et al., 2007; Davis and Weinstein, 2002). These studies generally conclude that cities experience quick economic recovery in the aftermath of military bombings. We posit that the explanation for this difference in response to man-made versus natural disasters is the expectation that certain areas will experience future natural disasters. This expectation of a spatial serial correlation in shock patterns means that those who supply capital to local governments or developers are likely to substitute away from these risky areas.

This paper finds that over the period 1982 to 2017, rating agencies did not appear to factor in ex ante hurricane risk into their assessment of municipal bonds. However, given that climate scientists predict hurricanes will increase in frequency and severity (Emanuel, 2017; Kossin et al., 2020), ratings agencies have an heightened incentive to invest resources in expanding their risk assessment capacities.

These adjustments are already beginning to manifest in the municipal debt market. Moody's Analytics purchased a climate risk intelligence firm in 2019 with the intent of incorporating environmental risk factors into their credit ratings analyses (Flavelle, 2019). This means that in future years municipal bond ratings may be more sensitive to hurricane and other climatic shocks. Our study suggests that this market capitalization of hurricane risk can exacerbate spatial inequality because poor and minority communities are less resilient to climate-related shocks.

Notably, most global economic activity is concentrated in coastal cities *despite* their vulnerability to natural disasters (Balboni, 2021). Our study highlights the vulnerability of local governments to climate shocks that have taken place over the last 40 years. Federal transfers have played an important role in partially insulating local government budgets. Climate scientists predict that areas along the Atlantic coast will experience even more severe hurricane shocks with greater maximum wind speeds and storm surge capacity going forward (Landsea and Knutson, 2022). The welfare implications of such shocks hinge on how the generosity of federal transfers programs change in response to these shocks.

References

Adelino, M., Cunha, I., and Ferreira, M. A. (2017). The economic effects of public financing: Evidence from municipal bond ratings recalibration. *The Review of Financial Studies*, 30(9):3223–3268.

Albouy, D. and Farahani, A. (2017). Valuing public goods more generally: The case of infrastructure.

Alm, J., Buschman, R. D., and Sjoquist, D. L. (2011). Rethinking local government reliance on the property tax. *Regional Science and Urban Economics*, 41(4):320–331.

Anderson, B., Schumacher, A., Guikema, S., Quiring, S., and Ferreri, J. (2020). *stormwindmodel: Model Tropical Cyclone Wind Speeds*. R package version 0.1.4.

Anttila-Hughes, J. and Hsiang, S. (2013). Destruction, disinvestment, and death: Economic and human losses following environmental disaster. *Available at SSRN 2220501*.

Bakkensen, L. A. and Ma, L. (2020). Sorting over flood risk and implications for policy reform. *Journal of Environmental Economics and Management*, page 102362.

Balboni, C. A. (2021). *In harm's way? infrastructure investments and the persistence of coastal cities*. PhD thesis, The London School of Economics and Political Science (LSE).

Banzhaf, H. S. and Walsh, R. P. (2008). Do people vote with their feet? an empirical test of tiebout. *American Economic Review*, 98(3):843–63.

Banzhaf, S., Ma, L., and Timmins, C. (2019). Environmental justice: The economics of race, place, and pollution. *Journal of Economic Perspectives*, 33(1):185–208.

Belasen, A. R. and Polachek, S. W. (2009). How disasters affect local labor markets the effects of hurricanes in florida. *Journal of Human Resources*, 44(1):251–276.

Bertinelli, L. and Strobl, E. (2013). Quantifying the local economic growth impact of hurricane strikes: An analysis from outer space for the caribbean. *Journal of Applied Meteorology and Climatology*, 52(8):1688–1697.

Betts, J. R. and Fairlie, R. W. (2001). Explaining ethnic, racial, and immigrant differences in private school attendance. *Journal of Urban Economics*, 50(1):26–51.

Billings, S. B., Gallagher, E. A., and Ricketts, L. (2022). Let the rich be flooded: the distribution of financial aid and distress after hurricane harvey. *Journal of Financial Economics*.

Blumberg, D. L. (2020). Cities brace for financial impact of covid-19.

Bolstad, P., Frank, S., Gesick, E., and Victor, D. (2020). Flying blind: What do investors really know about climate change risks in the us equity and municipal debt markets?

Borusyak, K., Jaravel, X., and Spiess, J. (2020). Revisiting event study designs: Robust and efficient estimation. Technical report, Working Paper.

Bosker, M., Brakman, S., Garretsen, H., and Schramm, M. (2007). Looking for multiple equilibria when geography matters: German city growth and the wwii shock. *Journal of Urban Economics*, 61(1):152–169.

Bourdeau-Brien, M. and Kryzanowski, L. (2017). The impact of natural disasters on the stock returns and volatilities of local firms. *The Quarterly Review of Economics and Finance*, 63:259–270.

Boustan, L. P., Kahn, M. E., Rhode, P. W., and Yanguas, M. L. (2020). The effect of natural disasters on economic activity in us counties: A century of data. *Journal of Urban Economics*, 118.

Brakman, S., Garretsen, H., and Schramm, M. (2004). The strategic bombing of german cities during world war ii and its impact on city growth. *Journal of Economic Geography*, 4(2):201–218.

Brigham, E. F. and Daves, P. R. (2015). *Intermediate financial management, 12th edition.* Cengage Learning.

Brooks, N. and Sethi, R. (1997). The distribution of pollution: community characteristics and exposure to air toxics. *Journal of environmental economics and management*, 32(2):233–250.

Cagle, J. A. (1996). Natural disasters, insurer stock prices, and market discrimination: The case of hurricane hugo. *Journal of Insurance Issues*, pages 53–68.

Callaway, B. and Sant'Anna, P. H. (2020). Difference-in-differences with multiple time periods. *Journal of Econometrics.*

Capeci, J. (1991). Credit risk, credit ratings, and municipal bond yields: A panel study. *National Tax Journal*, pages 41–56.

Chetty, R., Hendren, N., Kline, P., Saez, E., and Turner, N. (2014). Is the united states still a land of opportunity? recent trends in intergenerational mobility. *American Economic Review*, 104(5):141–47.

Christensen, P. and Timmins, C. (2021). The damages and distortions from discrimination in the rental housing market. Technical report, National Bureau of Economic Research.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of econometrics*, 92(1):1–45.

Cornaggia, J., Cornaggia, K. J., and Israelsen, R. D. (2018). Credit ratings and the cost of municipal financing. *The Review of Financial Studies*, 31(6):2038–2079.

Cromwell, E., Ihlanfeldt, K., et al. (2015). Local government responses to exogenous shocks in revenue sources: Evidence from florida. *National Tax Journal*, 68(2):339–376.

Davis, D. R. and Weinstein, D. E. (2002). Bones, bombs, and break points: the geography of economic activity. *American Economic Review*, 92(5):1269–1289.

Davlasheridze, M., Fisher-Vanden, K., and Allen Klaiber, H. (2017). The effects of adaptation measures on hurricane induced property losses: Which FEMA investments have the highest returns? *Journal of Environmental Economics and Management*, 81:93–114.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

del Valle, A., de Janvry, A., and Sadoulet, E. (2019). Rules for recovery: Impact of indexed disaster funds on shock coping in mexico. *American Economic Journal: Applied Economics*.

Delavega, E. (2021). Covid-19: This is how many americans now live below the poverty line.

Deryugina, T. (2017). The fiscal cost of hurricanes: Disaster aid versus social insurance. *American Economic Journal: Economic Policy*, 9(3):168–98.

Deryugina, T., Kawano, L., and Levitt, S. (2018). The economic impact of hurricane katrina on its victims: evidence from individual tax returns. *American Economic Journal: Applied Economics*, 10(2):202–33.

Deryugina, T. and Molitor, D. (2020). Does when you die depend on where you live? evidence from hurricane katrina. *American Economic Review*, 110(11):3602–33.

Driessen, J. (2005). Is default event risk priced in corporate bonds? *The Review of Financial Studies*, 18(1):165–195.

Eisensee, T. and Strömberg, D. (2007). News droughts, news floods, and us disaster relief. *The Quarterly Journal of Economics*, 122(2):693–728.

Elliott, R. J., Strobl, E., and Sun, P. (2015). The local impact of typhoons on economic activity in China: A view from outer space. *Journal of Urban Economics*, 88:50–66.

Emanuel, K. (2005). Increasing destructiveness of tropical cyclones over the past 30 years. *Nature*, 436(7051):686–688.

Emanuel, K. (2011). Global warming effects on US hurricane damage. *Weather, Climate, and Society*, 3(4):261–268.

Emanuel, K. (2017). Assessing the present and future probability of hurricane harvey's rainfall. *Proceedings of the National Academy of Sciences*, 114(48):12681–12684.

Farmer, L. (2015). Do credit ratings matter anymore? *Governing Magazine*.

Federal Reserve Board (2020). Municipal liquidity facility. Technical report, Board of Governors of the Federal Reserve System.

Feler, L. and Senses, M. Z. (2017). Trade Shocks and the Provision of Local Public Goods. *American Economic Journal: Economic Policy*, 9(4):101–143.

FEMA (2020). Disaster financial management guide: Guidance for state, local, tribal & territorial parterns. Technical report, FEMA.

Flavelle, C. (2019). Moody's buys climate data firm, signaling new scrutiny of climate risks. *The New York Times*.

Fowles, J., Liu, G., and Mamaril, C. B. (2009). Accounting for natural disasters: The impact of earthquake risk on california municipal bond pricing. *Public Budgeting & Finance*, 29(1):68–83.

Gallagher, J. and Hartley, D. (2017). Household finance after a natural disaster: The case of hurricane katrina. *American Economic Journal: Economic Policy*, 9(3):199–228.

Garrett, T. A. and Sobel, R. S. (2003). The political economy of fema disaster payments. *Economic inquiry*, 41(3):496–509.

Gaul, G. M. (2019). *The Geography of Risk: Epic Storms, Rising Seas, and the Cost of America's Coasts*. Sarah Crichton Books.

Glaeser, E. L., Kahn, M. E., and Rappaport, J. (2008). Why do the poor live in cities? the role of public transportation. *Journal of urban Economics*, 63(1):1–24.

Goldsmith-Pinkham, P. S., Gustafson, M., Lewis, R., and Schwert, M. (2021). Sea level rise and municipal bond yields. *Available at SSRN*.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*.

Gregory, J. (2013). The impact of post-katrina rebuilding grants on the resettlement choices of new orleans homeowners. *Unpublished manuscript*.

Groen, J., Kutzbach, M., and Polivka, A. (2016). Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term.

Groen, J. A., Kutzbach, M. J., and Polivka, A. E. (2020). Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *Journal of Labor Economics*, 38(3):653–685.

Hallstrom, D. G. and Smith, V. K. (2005). Market Responses to Hurricanes. *Journal of Environmental Economics and Management*, 50:541–561.

Hanna, B. G. (2007). House values, incomes, and industrial pollution. *Journal of Environmental Economics and Management*, 54(1):100–112.

Haughwout, A. F. (2002). Public infrastructure investments, productivity and welfare in fixed geographic areas. *Journal of public economics*, 83(3):405–428.

Healy, A. and Malhotra, N. (2009). Myopic voters and natural disaster policy. *American Political Science Review*, pages 387–406.

Holian, M. J. and Joffe, M. D. (2013). Assessing municipal bond default probabilities. *Available at SSRN 2258801*.

Hsiang, S. M. and Jina, A. S. (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Technical report, National Bureau of Economic Research.

Hubler, J., Louargant, C., Laroche, P., and Ory, J.-N. (2019). How do rating agencies' decisions impact stock markets? a meta-analysis. *Journal of Economic Surveys*, 33(4):1173–1198.

Irish, J. L., Resio, D. T., and Ratcliff, J. J. (2008). The influence of storm size on hurricane surge. *Journal of Physical Oceanography*, 38(9):2003–2013.

Jerch, R. (2020). The local benefits of federal mandates: Evidence from the clean water act. Technical report, Working Paper.

Kelly, M. (2019). The standard errors of persistence.

Kliger, D. and Sarig, O. (2000). The information value of bond ratings. *The journal of finance*, 55(6):2879–2902.

Knight, B. and Levinson, A. (1999). Rainy day funds and state government savings. *National Tax Journal*, pages 459–472.

Kossin, J. P., Knapp, K. R., Olander, T. L., and Velden, C. S. (2020). Global increase in major tropical cyclone exceedance probability over the past four decades. *Proceedings of the National Academy of Sciences*, 117(22):11975–11980.

Krueger, P., Sautner, Z., and Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3):1067–1111.

Lamb, R. P. (1995). An exposure-based analysis of property-liability insurer stock values around hurricane andrew. *Journal of Risk and Insurance*, pages 111–123.

Landsea, C. and Knutson, T. (2022). Can we expect atlantic hurricanes to change over the coming century due to global warming? Technical report, National Oceanic and Atmospheric Administration.

Liao, Y. and Kousky, C. (2022). The fiscal impacts of wildfires on california municipalities. *Journal of the Association of Environmental and Resource Economists*, 9(3).

Lin, G. C. (2019). High-skilled immigration and native task specialization in us cities. *Regional Science and Urban Economics*, 77:289–305.

Lis, E. M. and Nickel, C. (2010). The impact of extreme weather events on budget balances. *International Tax and Public Finance*, 17(4):378–399.

Lutz, B., Molloy, R., and Shan, H. (2011). The housing crisis and state and local government tax revenue: Five channels. *Regional Science and Urban Economics*, 41(4):306–319.

Lutz, B. F. (2008). The connection between house price appreciation and property tax revenues. *National Tax Journal*, pages 555–572.

Mahajan, P. and Yang, D. (2020). Taken by storm: Hurricanes, migrant networks, and us immigration. *American Economic Journal: Applied Economics*.

Masiero, G. and Santarossa, M. (2020). Earthquakes, grants, and public expenditure: How municipalities respond to natural disasters. *Journal of Regional Science*, 60(3):481–516.

Melecky, M. and Raddatz, C. (2011). *How do governments respond after catastrophes? Natural-disaster shocks and the fiscal stance*. The World Bank.

Melnik, W. (2017). Municipal government reaction to mass layoffs in ohio. Working Paper.

Miguel, E. and Roland, G. (2011). The long-run impact of bombing vietnam. *Journal of development Economics*, 96(1):1–15.

Mohai, P., Pellow, D., and Roberts, J. T. (2009). Environmental justice. *Annual review of environment and resources*, 34:405–430.

Molloy, R., Smith, C. L., and Wozniak, A. (2011). Internal migration in the united states. *Journal of Economic perspectives*, 25(3):173–96.

MSRB (2019). Muni facts. Technical report, Municipal Securities Rulemaking Board.

Muller, N. Z. and Hopkins, C. A. (2019). Hurricane Katrina Floods New Jersey: The Role of Information in the Market Response to Flood Risk. Working Paper 25984, National Bureau of Economic Research.

Notowidigdo, M. J. (2020). The incidence of local labor demand shocks. *Journal of Labor Economics*, 38(3):000–000.

Novy-Marx, R. and Rauh, J. (2014). The revenue demands of public employee pension promises. *American Economic Journal: Economic Policy*, 6(1):193–229.

Noy, I. and Nualsri, A. (2011). Fiscal storms: public spending and revenues in the aftermath of natural disasters. *Environment and Development Economics*, 16(1):113–128.

Noy, I., Okubo, T., Strobl, E., and Tveit, T. (2021). The fiscal costs of earthquakes in japan.

Ortega, F. and Taṣpinar, S. (2018). Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market. *Journal of Urban Economics*, 106:81–100.

Ouattara, B. and Strobl, E. (2013). The fiscal implications of hurricane strikes in the caribbean. *Ecological Economics*, 85:105–115.

Ouazad, A. and Kahn, M. E. (2019). Mortgage finance in the face of rising climate risk. Technical report, National Bureau of Economic Research.

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*, 135(2):468–482.

Ratnadiwakara, D. and Venugopal, B. (2020). Do areas affected by flood disasters attract lower-income and less creditworthy homeowners? *Journal of Housing Research*, 29(sup1):S121–S143.

Riley, K. (2020). States workt o fund costly bridge repairs, replacements.

Rubinfeld, D. (1973). Credit ratings and the market for general obligation municipal bonds. *National Tax Journal*, pages 17–27.

Sangiorgi, F., Sokobin, J., and Spatt, C. (2009). Credit-rating shopping, selection and the equilibrium structure of ratings. Technical report, Working Paper, Stockholm School of Economics and Carnegie Mellon University.

Schwert, M. (2017). Municipal bond liquidity and default risk. *The Journal of Finance*, 72(4):1683–1722.

Shoag, D., Tuttle, C., and Veuger, S. (2019). Rules versus home rule: Local government responses to negative revenue shocks. *National Tax Journal*, 72(3):543–547.

Skidmore, M. and Scorsone, E. (2011). Causes and consequences of fiscal stress in michigan cities. *Regional Science and Urban Economics*, 41(4):360–371.

Skidmore, M. and Toya, H. (2002). Do natural disasters promote long-run growth? *Economic inquiry*, 40(4):664–687.

Stein, J. and Van Dam, A. (2019). Taxpayer spending on u.s. disaster fund explodes amid climate change, population trends.

Strambaugh, H. and Sensenig, D. (2008). Special report: Fire department preparedness for extreme weather emergencies and natural disasters. Technical report, FEMA.

Strobl, E. (2010). The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties. *Review of Economics and Statistics*, 93(2):575–589.

Tran, B. R. and Wilson, D. J. (2020). The local economic impact of natural disasters.

Unterberger, C. (2018). How flood damages to public infrastructure affect municipal budget indicators. *Economics of disasters and climate change*, 2(1):5–20.

Urahn, S. K. and Irwin, M. (2020). How states pay for natural disasters in an era of rising costs. Technical report, The Pew Charitable Trusts.

Vigdor, J. (2008). The economic aftermath of hurricane katrina. *Journal of Economic Perspectives*, 22(4):135–54.

Willoughby, H., Darling, R., and Rahn, M. (2006). Parametric representation of the primary hurricane vortex. part ii: A new family of sectionally continuous profiles. *Monthly weather review*, 134(4):1102–1120.

Witte, L. R. and Gurwitz, Z. R. (2018). Default, transition, and recovery: 2018 annual u.s. public finance default study and rating transitions. Technical report, Standard & Poors Global Ratings.

Worthington, A. and Valadkhani, A. (2004). Measuring the impact of natural disasters on capital markets: an empirical application using intervention analysis. *Applied Economics*, 36(19):2177–2186.

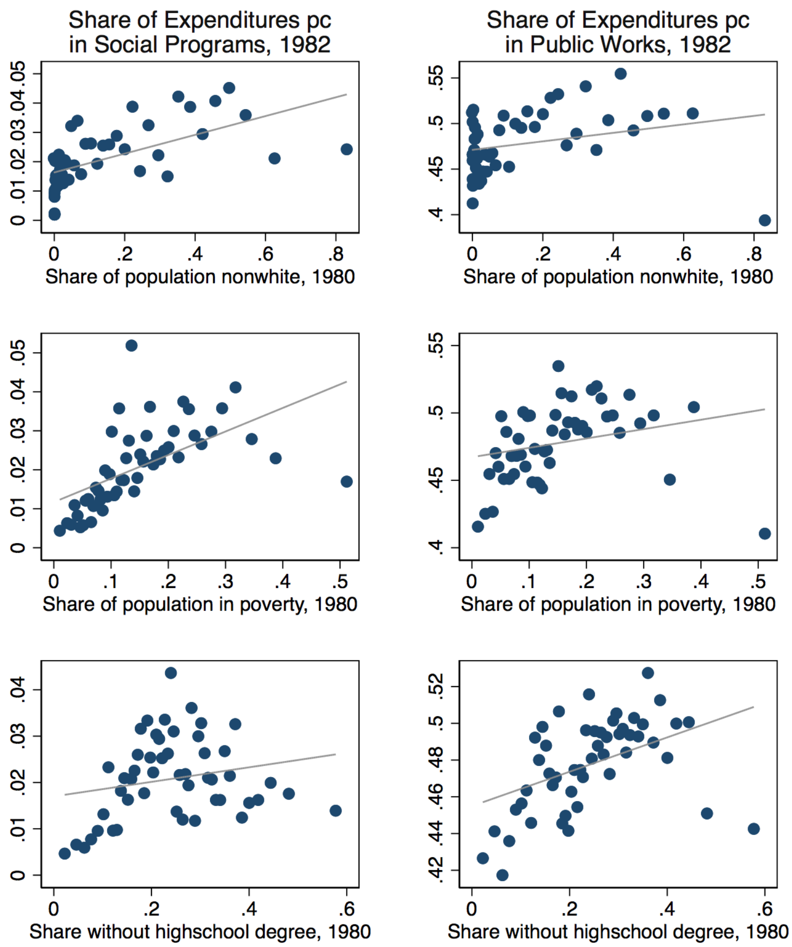


Figure 1: Provision of Local Public Goods & Demographic Composition

Note: Figure plots the mean share of per capita local government expenditures as of 1982 for each of 50 bins describing local demographic composition. Demographic characteristics measured as of 1980. Each dot represents approximately 130 general purpose governments. All means residualized by the 1980 local government population. "Social Programs" include expenditures in public welfare, hospitals, health, housing, and unemployment compensation. "Public Works" includes expenditures in transportation, water, sewer, trash, parks & rec, and the environment. Source: Census of Governments; NHGIS.

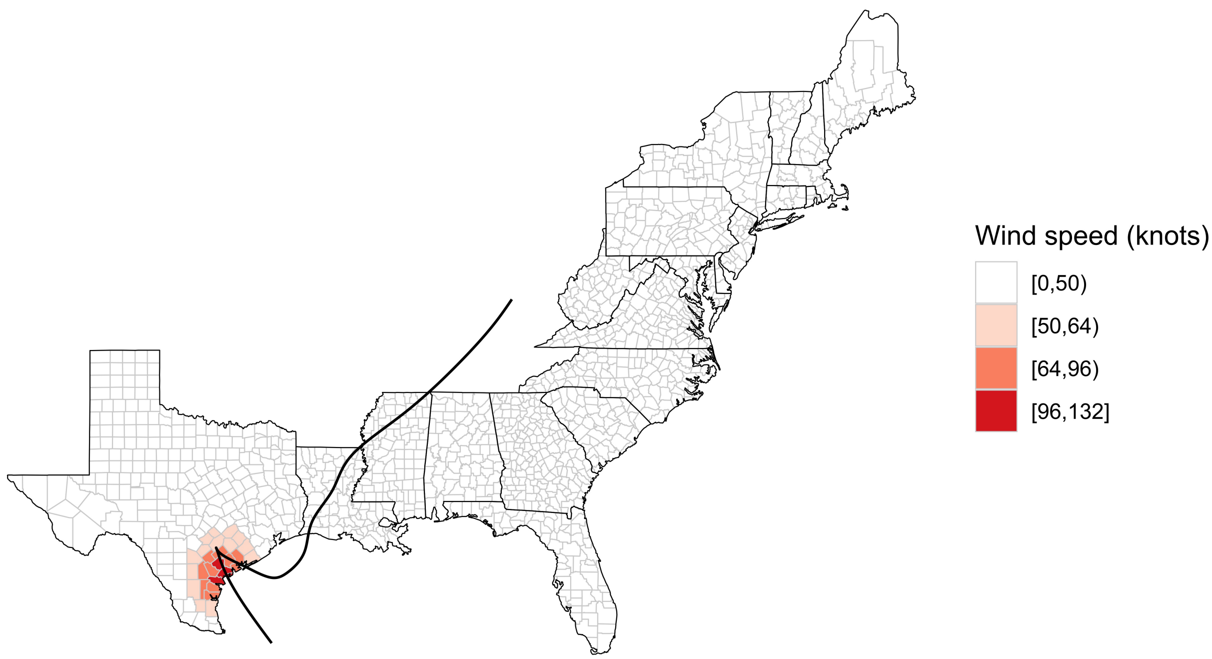
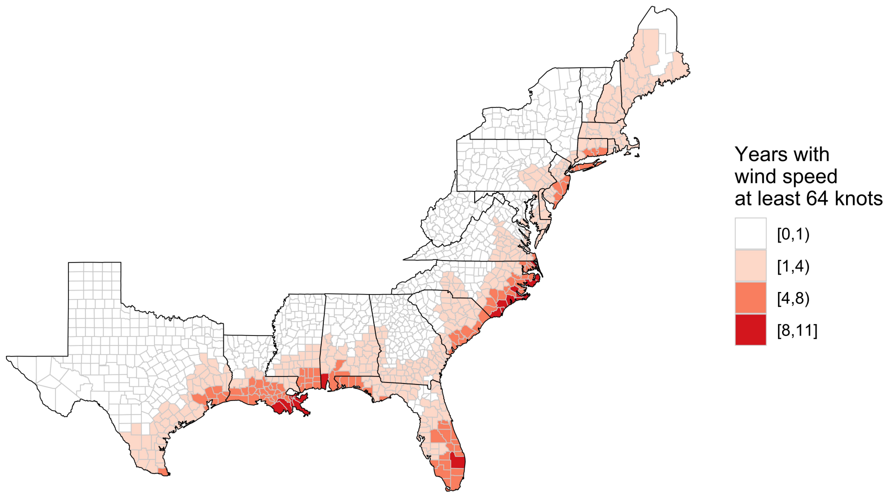
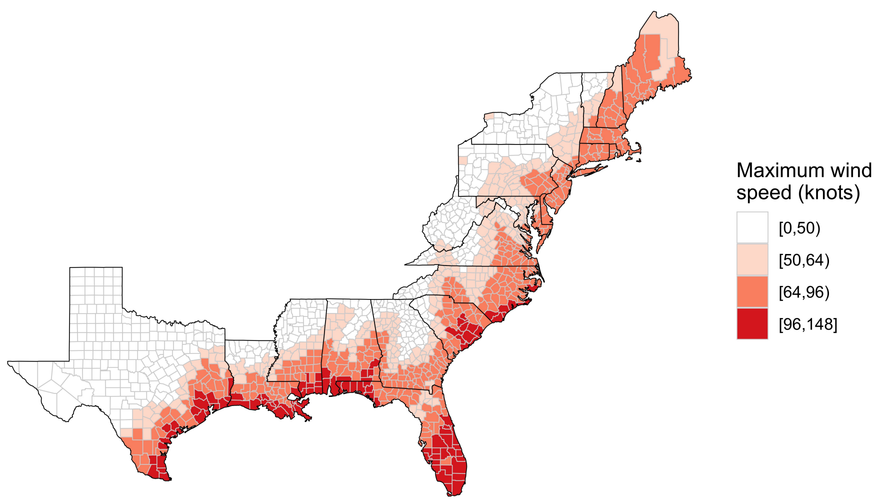


Figure 2: Estimated Wind Speeds of Hurricane Harvey

Note: Figure plots the storm path of Hurricane Harvey in 2017 (in black) and the estimated county-level maximum wind speeds. Source: Authors' calculations from the HURDAT2 Atlantic hurricane database.



A. Number of years counties experienced hurricane-strength winds



B. Maximum wind speed experienced by counties

Figure 3: Geographic Distribution of Hurricane Events by Frequency & Intensity, 1972–2017

Note: Panel A plots the geographic distribution of the number of years that counties experienced at least 64 kts winds. Panel B plots the county-level distribution of maximum wind speeds. Source: Authors' calculations from the HURDAT2 Atlantic hurricane database.

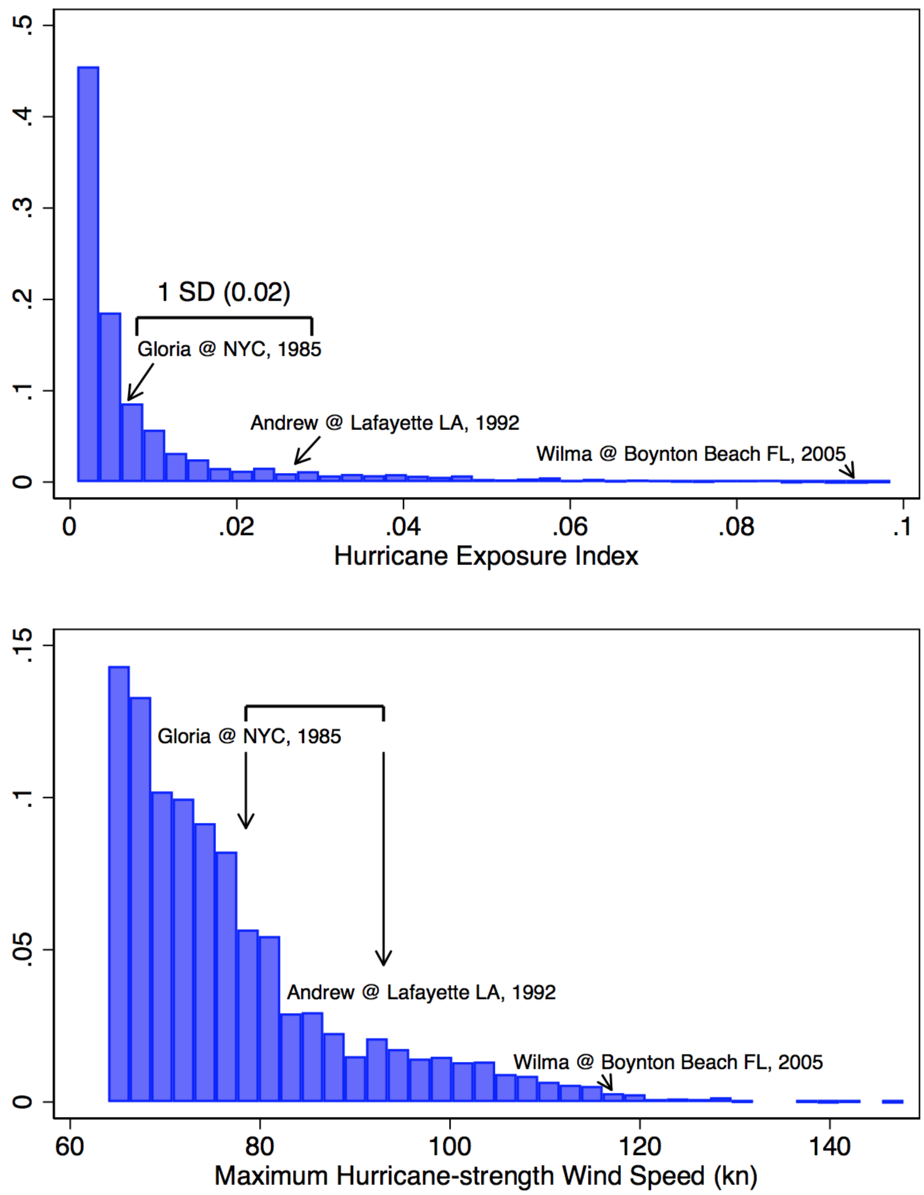


Figure 4: Distribution of Municipal Hurricane Exposure Index, 1972-2017

Note: Panel A shows the distribution of the hurricane exposure index. The y-axis measures the fraction of observations with a given exposure index. For ease of exposition, we plot the distribution only for index values below 0.1. (The largest exposure index value in our data is 0.28 experienced in Coral Gables, FL in 1992 due to Hurricane Andrew). A standard deviation change in the index (an increase of 0.02) is equivalent to the change in damage experienced in NYC in 1985 from Hurricane Gloria relative that of Lafayette, LA from Hurricane Andrew in 1992. See Appendix A for details on the index calculation. Panel B shows the distribution of maximum hurricane-strength wind speed (wind speeds over 64 knots). The y-axis measures the fraction of observations with a wind speed. We show the 1 SD change in the index from Panel A translated to maximum wind speed: Lafayette, LA experienced wind speeds of 93.6 kn in 1992 whereas NYC experienced wind speeds of 78.6 in 1985. Source: Authors' calculations from the HURDAT2 Atlantic hurricane database.

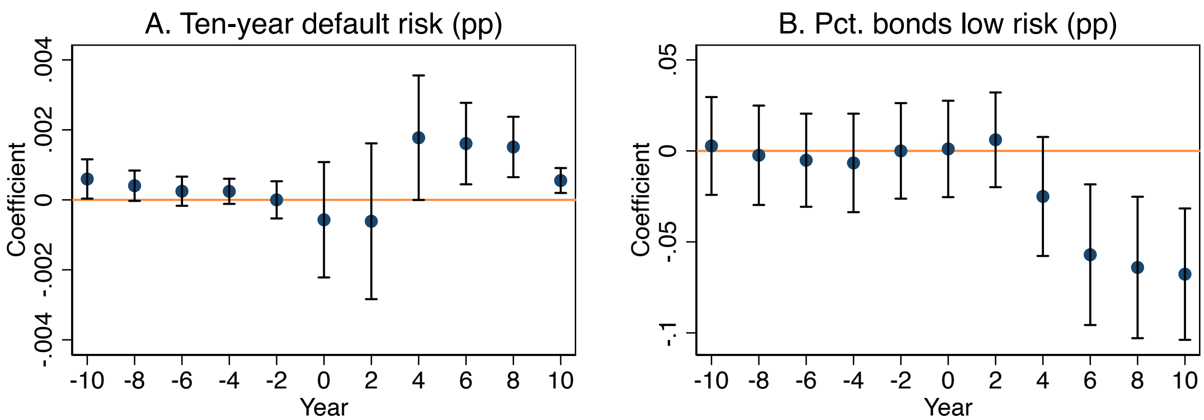


Figure 5: Hurricanes and Municipal Bond Rating Dynamics, 1982–2009

Note: Figure plots the estimates and 95% confidence intervals using Equation 5. Coefficients are normalized by subtracting from them the binned "Year -2" coefficient.

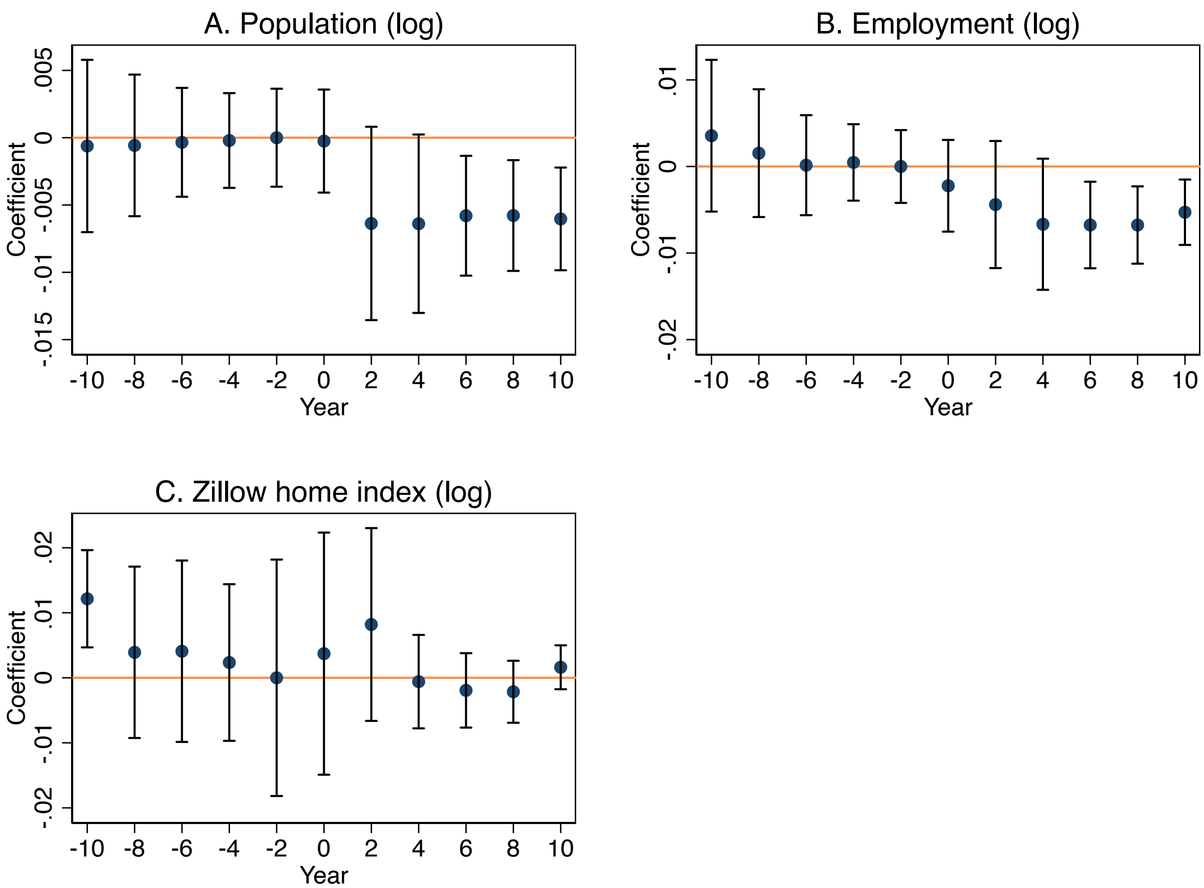


Figure 6: Hurricanes and County Population, Employment, and Home Value Dynamics, 1982–2009

Note: Figure plots the estimates and 95% confidence intervals using Equation 5. Coefficients are normalized by subtracting from them the binned "Year -2" coefficient.

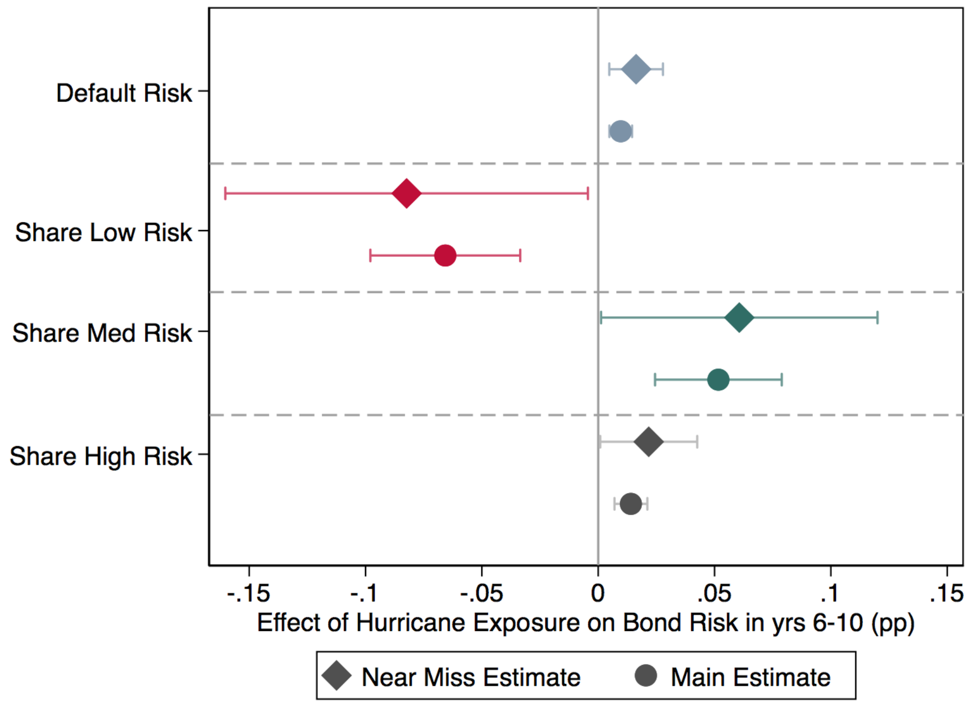


Figure 7: Neighboring Municipality Analysis vs Main Analysis

Note: Figure plots coefficient estimates and 95% confidence intervals of β_2 from Eq. 3, the effect of a 1 SD change in hurricane wind speed 6-10 years after exposure. Diamonds show estimates from a "neighboring municipality" analysis where we compare exposed municipalities to municipalities in bordering counties that were not exposed to the same major hurricane-strength winds. Circles show estimates from Table 4, columns 1-4. Each coefficient is estimated from a separate regression. Outcomes include the 10-year default risk, and the share of bonds rated low risk, medium risk, and high risk, respectively. Default risk coefficients are in a tenth-of-a-percentage-point units. Coefficients are provided in tabular form in Appendix Table B.3.

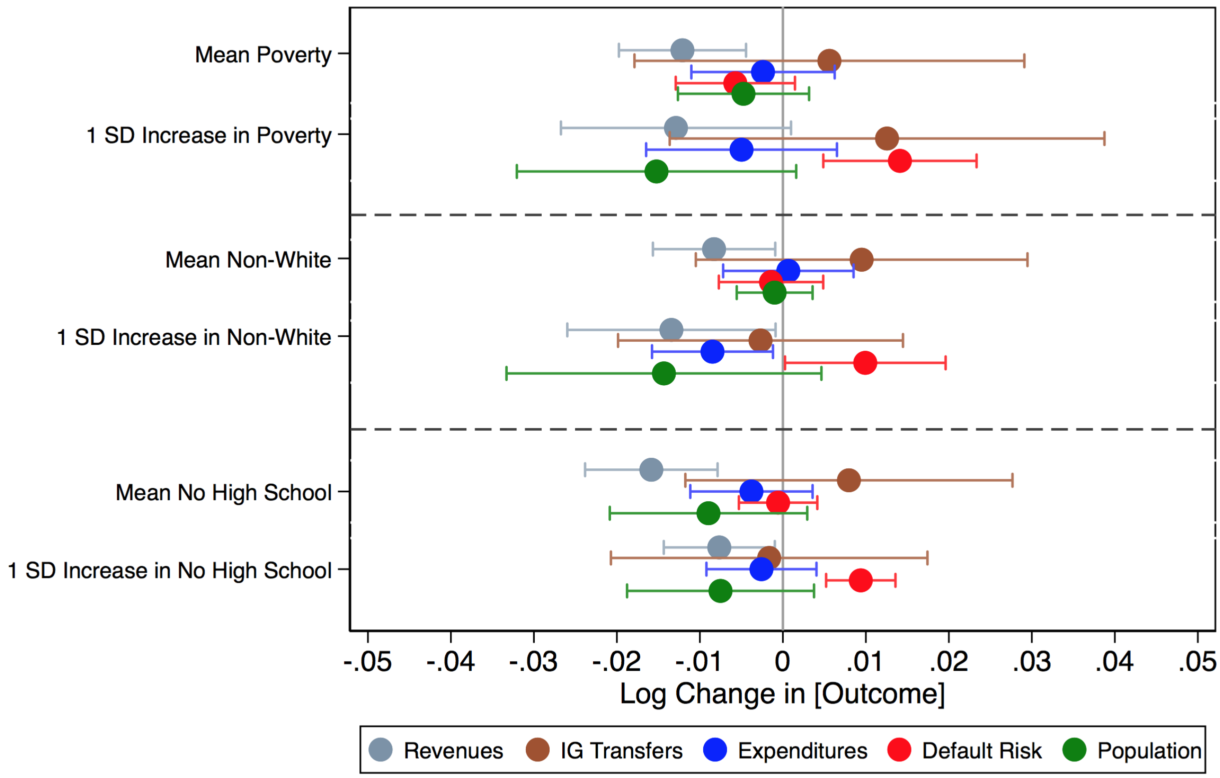


Figure 8: Fiscal Effects of Hurricanes by Demographic Attributes, 1982–2017

Note: Figure plots the estimates and 95% confidence intervals of κ_1 and κ_2 from $y_{ist} = \kappa_1 H_{it}^{1-10} + \kappa_2(H_{it}^{1-10} \times D_{i,1970}) + \alpha_i + \alpha_{st} + \delta'(\mathbf{X}_i\alpha_t) + \varepsilon_{ist}$ where $D_{i,1970}$ measures one of three (demeaned) demographic attributes of municipality i as of 1970: poverty rate, share of population that is non-white, and share of population without a high school degree. Outcomes y include ln(revenues), ln(intergovernment transfers), ln(expenditures), 10-year default risk, and ln(population). Default risk is not in logs. Default risk coefficient are in a tenth-of-a percentage-point units. Estimates of κ_1 and κ_2 are estimated from one regression per demographic attribute. κ_1 measures the change in outcome y in the 10 years after hurricane exposure for municipalities with average levels of demographic attributes. κ_2 measures the additional effect of hurricanes on outcome y for a one standard deviation increase in an attribute. All other controls are the same as Eq. 3. Controls include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Standard errors are clustered at the county level.

Table 1: Summary Statistics

	Hurricane	Non-Hurricane	P-val
Panel A: 1970 Municipality Characteristics			
Population	15,833.170	5,869.551	0.000
Land Area	8.302	5.021	0.000
Share 25 and older pop. less than high school	0.329	0.344	0.000
Share pop. nonwhite	0.171	0.104	0.000
Share pop. in poverty	0.163	0.148	0.000
Panel B: Budget Characteristics (Annual $mn.)			
Total Revenues	84.161	15.502	0.000
Own Source	60.607	12.654	0.000
Tax	32.625	4.895	0.000
Other Revenues	21.651	7.257	0.000
Total Intergov.	23.554	2.848	0.000
Federal Intergov.	3.737	0.594	0.000
State & Local Intergov.	19.817	2.254	0.000
Total expenditures	83.175	15.394	0.000
Education	15.661	1.302	0.000
Safety	10.883	2.590	0.000
Public works	22.587	7.445	0.000
Social programs	14.345	0.802	0.000
G&A	3.418	0.965	0.000
Other expenditures	16.281	2.290	0.000
Total out. debt	76.432	18.407	0.000
Long-term debt issued	11.384	2.685	0.000
Long-term debt retired	7.388	1.842	0.000
Panel C: Bond Characteristics			
Default Rate (10-yr horizon)	0.002	0.003	0.004
Share of medium risk bonds	0.232	0.308	0.000
Share of high risk bonds	0.012	0.011	0.753
Number of governments	2,181	3,963	
Observations	17,448	31,704	

Note: The unit of observation is a municipal government-year. Data describes mean municipal attributes from 1982 through 2017. Budget values measured in 2017 USD. Panel A characteristics measured as of 1970. Sourced from US Census. Panel B data sourced from Census of Governments. Panel C data sourced from Moody's Analytics. Among the 6,144 municipalities in the Census of Governments Data, 581 appear in the Moody's data (311 are ever exposed to a hurricane between 1972 and 2017 and 270 are not).

Table 2: Effect of Hurricanes on Municipal Government Revenues, 1982–2017.

Dependent variable: revenues (log)	Total revenues (1)	Own-source revenues: Total own-source revenues (2)	Own-source revenues: Taxes (3)	Own-source revenues: Other revenues (4)	Intergov. transfers: Total transfers (5)	Intergov. transfers: Federal (6)	Intergov. transfers: State & local (7)
Panel A. Hurricane wind speed							
1 SD hurricane wind in last 1–5 years	-0.003	-0.007	-0.007	0.004	0.023**	0.065	0.006
	(0.005)	(0.006)	(0.007)	(0.007)	(0.011)	(0.071)	(0.019)
1 SD hurricane wind in last 6–10 years	-0.016***	-0.020***	-0.012**	0.009	-0.004	0.100	-0.016
	(0.005)	(0.006)	(0.005)	(0.007)	(0.015)	(0.080)	(0.013)
Panel B. Hurricane category							
Max wind speed $\geq$ 64 kts and $<$ 96 kts in last 1–5 years (=1)	-0.013	-0.035***	-0.023	-0.002	0.044	0.026	0.010
	(0.010)	(0.013)	(0.015)	(0.022)	(0.032)	(0.120)	(0.035)
Max wind speed $\geq$ 64 kts and $<$ 96 kts in last 6–10 years	-0.006	-0.030***	-0.048***	-0.008	0.054	0.161	0.007
	(0.013)	(0.012)	(0.014)	(0.019)	(0.033)	(0.108)	(0.042)
Max wind speed $\geq$ 96 kts in last 1–5 years (=1)	-0.033	-0.062**	-0.047	-0.007	0.099	0.189	0.044
	(0.027)	(0.030)	(0.037)	(0.032)	(0.066)	(0.360)	(0.077)
Max wind speed $\geq$ 96 kts in last 6–10 years (=1)	-0.047**	-0.072***	-0.084***	0.006	-0.035	0.270	-0.028
	(0.022)	(0.026)	(0.032)	(0.035)	(0.085)	(0.397)	(0.065)
Observations	49152	49152	49152	49152	49152	49152	49152

Note: Outcomes are log revenues. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Standard errors are clustered at the county level.

Table 3: Effect of Hurricanes on Municipal Government Expenditures, 1982–2017.

Dependent variable: expenditures (log)	Total (1)	Public works (2)	Public safety (3)	Misc. (4)	Gov. admin. (5)
Panel A. Hurricane wind speed					
1 SD hurricane wind in last 1–5 years	0.005	-0.001	0.009	0.002	0.025***
	(0.004)	(0.009)	(0.007)	(0.010)	(0.007)
1 SD hurricane wind in last 6–10 years	-0.010*	-0.034***	-0.005	0.002	0.012*
	(0.005)	(0.007)	(0.008)	(0.015)	(0.006)
Panel B. Hurricane category					
Max wind speed $\geq$ 64 kts and $<$ 96 kts in last 1–5 years (=1)	-0.001	-0.008	0.013	-0.032	0.021
	(0.010)	(0.020)	(0.016)	(0.026)	(0.022)
Max wind speed $\geq$ 64 kts and $<$ 96 kts in last 6–10 years	-0.001	-0.024	-0.032	-0.069***	-0.008
	(0.011)	(0.029)	(0.026)	(0.025)	(0.030)
Max wind speed $\geq$ 96 kts in last 1–5 years (=1)	-0.009	-0.062	0.030	0.021	0.100**
	(0.024)	(0.041)	(0.036)	(0.056)	(0.045)
Max wind speed $\geq$ 96 kts in last 6–10 years (=1)	-0.059**	-0.137***	-0.040	-0.070	0.055
	(0.029)	(0.048)	(0.038)	(0.054)	(0.046)
Observations	49152	49152	49152	49152	49152

Note: Outcomes are log expenditures. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Standard errors are clustered at the county level.

Table 4: Effect of Hurricanes on Municipal Debt, 1982–2012.

Dependent variable: municipal bond ratings and municipal debt	Municipal bond ratings				Municipal government debt		
	Ten-year default risk (pp) (1)	Pct. bonds low risk (pp) (2)	Pct. bonds medium risk (pp) (3)	Pct. bonds high risk (pp) (4)	Total debt outstanding (log) (5)	Long-term debt issued (log) (6)	Long-term debt retired (log) (7)
Panel A. Hurricane wind speed							
1 SD hurricane wind in last 1–5 years	0.001**	-0.023**	0.006	0.017***	-0.009	-0.224	-0.004
	(0.000)	(0.011)	(0.008)	(0.005)	(0.022)	(0.230)	(0.023)
1 SD hurricane wind in last 6–10 years	0.001***	-0.066***	0.052***	0.014***	-0.031*	-0.285	-0.030
	(0.000)	(0.016)	(0.014)	(0.004)	(0.017)	(0.220)	(0.106)
Panel B. Hurricane category							
Max wind speed $\geq$ 64 kts and $<$ 96 kts in last 1–5 years (=1)	-0.001**	0.035	-0.005	-0.030**	-0.102*	0.162	0.077
	(0.001)	(0.037)	(0.035)	(0.013)	(0.054)	(0.358)	(0.091)
Max wind speed $\geq$ 64 kts and $<$ 96 kts in last 6–10 years (=1)	-0.001*	0.050	-0.020	-0.030***	-0.126***	0.649*	0.025
	(0.001)	(0.038)	(0.034)	(0.011)	(0.047)	(0.361)	(0.078)
Max wind speed $\geq$ 96 kts in last 1–5 years (=1)	0.005**	-0.127*	0.034	0.092***	-0.192**	0.051	0.109
	(0.002)	(0.067)	(0.049)	(0.033)	(0.093)	(0.770)	(0.108)
Max wind speed $\geq$ 96 kts in last 6–10 years (=1)	0.005**	-0.291***	0.226**	0.065***	-0.259***	-0.266	0.186
	(0.002)	(0.111)	(0.092)	(0.024)	(0.069)	(0.889)	(0.306)
Observations	9943	9943	9943	9943	4067	4067	4067

Note: Outcomes are municipal bond ratings, total debt outstanding, and debt issuance and retirement. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Columns (1) through (4) also include controls for mean bond characteristics (coupon rate, share of bonds that are general obligation, share of bonds sold at public auction, and maturity length). Standard errors are clustered at the county level.

Table 5: Effect of Hurricanes on Local Population Dynamics.

Dependent variable: population, employment, and home value index (log)	Population (1)	Population (2)	Employment (3)	Home value index (4)
Panel A. Hurricane wind speed				
1 SD hurricane wind in last 1–5 years	-0.008	-0.003	-0.005**	-0.011***
	(0.007)	(0.002)	(0.002)	(0.003)
1 SD hurricane wind in last 6–10 years	-0.007*	-0.002	-0.005***	-0.010***
	(0.004)	(0.002)	(0.002)	(0.003)
Panel B. Hurricane category				
Max wind speed $\geq$ 64 kts and < 96 kts in last 1–5 years (=1)	-0.009	0.001	-0.005	-0.040***
	(0.008)	(0.006)	(0.007)	(0.012)
Max wind speed $\geq$ 64 kts and < 96 kts in last 6–10 years	-0.030***	-0.002	-0.004	0.001
	(0.010)	(0.006)	(0.008)	(0.010)
Max wind speed $\geq$ 96 kts in last 1–5 years (=1)	-0.069*	-0.043**	-0.045**	-0.057**
	(0.037)	(0.021)	(0.019)	(0.023)
Max wind speed $\geq$ 96 kts in last 6–10 years (=1)	-0.057**	-0.036**	-0.039**	-0.039*
	(0.024)	(0.017)	(0.019)	(0.020)
Treatment unit	Muni. gov.	County	County	County
Observations	49152	45504	45504	19187

Dependent variable: municipal demographics	Poverty Rate (1)	Share of population non-white (2)	Unemployment rate (3)
Panel C. Hurricane wind speed			
1 SD hurricane wind in last 1–10 years	0.001**	0.001	0.002***
	(0.000)	(0.001)	(0.000)
Panel D. Hurricane category			
Max wind speed $\geq$ 64 kts and < 96 kts in last 1–10 years (=1)	0.007***	0.004	0.001
	(0.002)	(0.004)	(0.001)
Max wind speed $\geq$ 96 kts in last 1–10 years (=1)	0.015***	0.001	0.006**
	(0.004)	(0.006)	(0.003)
Treatment unit	Muni. gov.	Muni. gov.	Muni. gov.
Observations	18421	18421	18421

Note: In Panels A and B, outcomes are log municipality population, log county population, log county employment, and log Zillow county home value index. Column 1 controls for municipality covariates and municipal government fixed effects; Columns 2 to 4 control for county covariates and county fixed effects. The sample period is from 1982 to 2017 except for Column 4 which is from 1996 to 2017.
In Panels C and D, outcomes are poverty rate, share of the population that is non-white, and the unemployment rate. In all panels, control variables include interactions of year dummies with a vector of 1970 municipality or county characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government or county fixed effects as noted by the treatment unit, and state-by-year fixed effects. Standard errors are clustered at the county level.

Table 6: Effect of Hurricanes on Municipal Government Per Capita Finances, 1982–2017.

		Own-source revenues			Intergov. transfers		
Panel A. Dependent variable: per capita revenues (log)	Total revenues (1)	Total own-source revenues (2)	Taxes (3)	Other revenues (4)	Total transfers (5)	Federal (6)	State & local (7)
1 SD hurricane wind in last 1–5 years	0.005	0.001	0.001	0.012*	0.031**	0.066*	0.015
	(0.005)	(0.005)	(0.005)	(0.007)	(0.013)	(0.037)	(0.019)
1 SD hurricane wind in last 6–10 years	-0.009	-0.013**	-0.005	0.016**	0.002	0.058	-0.008
	(0.007)	(0.007)	(0.003)	(0.008)	(0.014)	(0.045)	(0.012)
Observations	49152	49152	49152	49152	49152	49152	49152

	Expenditures					Debt	
Panel B. Dependent variable: per capita expenditures & debt (log)	Total (1)	Public works (2)	Public safety (3)	Misc. (4)	Gov. admin. (5)	Total debt outstanding (log) (6)	Long-term debt issued (log) (7)
1 SD hurricane wind in last 1–5 years	0.013***	0.007	0.016*	0.011	0.033***	0.017	-0.047
	(0.005)	(0.006)	(0.009)	(0.012)	(0.009)	(0.022)	(0.107)
1 SD hurricane wind in last 6–10 years	-0.003	-0.026***	0.001	0.006	0.019***	0.001	-0.108
	(0.006)	(0.008)	(0.008)	(0.013)	(0.007)	(0.021)	(0.101)
Observations	49152	49152	49152	49152	49152	45144	45144

Note: Outcomes are log revenues, expenditures, or debt per capita. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Standard errors are clustered at the county level.

A Data Description and Variable Definitions

A.1 Census of Governments

Below is the list of the individual components of the six broad expenditure categories:

- Education expenditures: total spending on primary, secondary, and postsecondary education.
- Government administration: local government finance, general public buildings, judicial and legal, and central staff services.
- Miscellaneous expenditures: interests on debt, liquor stores, miscellaneous commercial activities, insurance trusts, and other general expenditures.
- Public assistance: public welfare, public housing, hospital and health, and employment security administration.
- Public works: sewer, water, trash, parks and recreational, the environment, housing, transportation, and total utilities.
- Public safety: police, fire, correctional facilities, and protective inspection.

A.2 Hurricane Exposure

The Atlantic HURDAT2 dataset contains all known tropical and subtropical cyclones between 1851 and 2019. We supplement it with the Extended Best Track dataset that begins in 1988 and ends in 2018. We consider all storm events with wind speeds at least 64 kts at some point on the storm tracks.

Using the storm tracks, we construct a measure of local jurisdictions' hurricane exposure in four steps. First, for each storm, we use the storm tracks to predict the maximum wind speed experienced at each census tract centroid.[46] Second, for each year, we use the maximum predicted wind speed at each census tract centroid to calculate the potential economic damage of hurricanes. Similar to Emanuel (2011), we assume that the damage function is a cubic function of wind speed and tropical cyclones with wind speeds below the 50 kts threshold do not cause economic damage. For census tract j in jurisdiction k in year t, the potential damage is given by

$$damage_{jkt} = \frac{\max(Wind_{jkt} - 50, 0)^3}{MaxWind^3}, \tag{6}$$

where $Wind_{jkt}$ is the maximum wind speed in census tract j in jurisdiction k in year t and $MaxWind$ is the maximum wind speed observed in the sample between 1972 and 2017. Rescaling by $MaxWind$ is purely for aesthetic purposes as it reduces the number of leading zeros in the estimates. Third,

[46] Storm tracks and wind speeds are estimated using Anderson et al. (2020). They parametrically estimate wind speeds at grid points as a decreasing function of distance to the storm center based on the model of Willoughby et al. (2006). They further reduce wind speeds by a factor of 0.8 to take into account surface friction over land. We remove this surface friction component in the exposure measure by multiplying the estimated wind speeds by the reciprocal of 0.8. We remove this surface friction component (1) in order to utilize a wind speed measure consistent with Willoughby et al. (2006)'s original climate model and (2) because the inclusion of this component leads to severe misclassifying of major hurricanes. Because we multiply all wind speeds by the same factor, our results using the hurricane index are unlikely to be affected by this choice.

we approximate the economic shock experienced by the local jurisdiction in a given year or in a given time period using the most severe storm in that time frame; i.e., we assume

$$H_{kt} = \max_{j} damage_{jkt}., \tag{7}$$

where the maximum is taken over all census tract centroids in a jurisdiction k. In instances where census tracts overlap city boundaries, we allocate census tract population to cities based a crosswalk provided by Missouri Census Data Center's "MABLE/Geocorr 2000."

B Additional Tables

Table B.1: Total Impact of Hurricane Exposure on Municipal Finances (present discounted value)

	Windspeed (1)	Minor Hurricanes (2)	Major Hurricanes (3)
Panel A. Level Impacts ($)			
Total Revenues	-2,439,445.6	-2,909,493.3	-11,148,884
Own-Source Revenues	-2,780,338.6	-7,079,420.3	-14,014,646
Intergov't Transfers	895,005.194	3,710,740.7	3,382,729
Total Expenditures	-412,827.802	-359,122.402	-8,637,761.5
Public Works Expenditures	-1,410,979.1	-1,348,988.8	-8,400,394.7
Panel B. Per Capita Impacts ($)			
Total Revenues	-8.5	88	291
Own-Source Revenues	-48	-140	-21
Intergov't Transfers	40	140	231
Total Expenditures	68	182	377
Public Works Expenditures	-39	40	-149

Note: This table shows the present discounted value of changes to local government finances in the 1 to 10 years after hurricane exposure. Assumed interest rate is 6%, based on the yield of 1-year constant maturity US Treasury Securities as of January 2000. Calculations in columns (1), and (2) and (3) use parameter estimates from Eq. 3 and Eq. 4, respectively. I follow Deryugina (2017) to calculate the present value (PV) as follows: $PV = \sum_{t=1}^{10} \frac{1}{(1+r)^t}(e^{\mu+\hat{\beta}_t} - e^{\mu})$ where μ is the mean of a particular outcome, such as the log of total revenues, and $\hat{\beta}$ is the estimated effect of a hurricane in year t. We restrict certain coefficients to be equal to each other in our empirical approach. Consequently, when we calculate the PV, we set $\hat{\beta}_1$ through $\hat{\beta}_5$ as equal to each other (the year 1 through 5 coefficient estimate) and likewise $\hat{\beta}_6$ through $\hat{\beta}_{10}$ to be equal to each other (the year 6 through 10 coefficient estimate).

Table B.2: Effect of Hurricanes on Municipal Tax Subcategories, Additional Expenditure Categories, and Employment and Payroll, 1982–2017.

Dependent variable: public finance and public employment outcomes (log)	Property taxes (1)	Sales, income, license, & n.e.c taxes (2)	Public educ. (3)	Public assistance (4)	Public emp. (5)	Full-time equivalent public emp. (6)	Public payroll (7)
1 SD hurricane wind in last 1–5 years	-0.001	-0.010	0.001	-0.053*	-0.018***	-0.015***	-0.012**
	(0.006)	(0.010)	(0.033)	(0.028)	(0.006)	(0.006)	(0.006)
1 SD hurricane wind in last 6–10 years	-0.010	-0.003	0.012	0.017	-0.015***	-0.015***	-0.013**
	(0.007)	(0.011)	(0.053)	(0.031)	(0.005)	(0.006)	(0.006)
Observations	49152	49152	49152	49152	49152	49152	49152

Note: Outcomes are log taxes, expenditures, public employment and payroll. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Standard errors are clustered at the county level.

Table B.3: Neighboring Municipality Analysis: Effect of Hurricanes on Municipal Debt, 1982–2012.

Dependent variable: municipal bond ratings (pp)	Ten-year default risk (1)	Pct. bonds low risk (2)	Pct. bonds medium risk (3)	Pct. bonds high risk (4)
Panel A. Hurricane wind speed				
1 SD hurricane wind in last 1–5 years	0.003**	-0.069**	0.045*	0.024*
	(0.001)	(0.026)	(0.022)	(0.012)
1 SD hurricane wind in last 6–10 years	0.002***	-0.082**	0.061**	0.022**
	(0.001)	(0.038)	(0.029)	(0.010)
Panel B. Hurricane category				
Max wind speed $\geq$ 64 kts and $<$ 96 kts in last 1–5 years (=1)	0.001	-0.107***	0.120***	-0.013
	(0.002)	(0.037)	(0.038)	(0.014)
Max wind speed $\geq$ 64 kts and $<$ 96 kts in last 6–10 years (=1)	-0.001	-0.045	0.057	-0.012
	(0.001)	(0.056)	(0.065)	(0.015)
Max wind speed $\geq$ 96 kts in last 1–5 years (=1)	0.013*	-0.288**	0.224*	0.064
	(0.007)	(0.131)	(0.121)	(0.038)
Max wind speed $\geq$ 96 kts in last 6–10 years (=1)	0.001	-0.147	0.127	0.020
	(0.004)	(0.127)	(0.115)	(0.024)
Observations	919	919	919	919

Note: Outcomes are municipal bond ratings. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipality group fixed effects, and year fixed effects; as well as controls for mean bond characteristics (coupon rate, share of bonds that are general obligation, share of bonds sold at public auction, and maturity length). Standard errors are clustered at the county level.

Table B.4: Fiscal Effects of Hurricanes by Historical Demographic Attributes, 1982–2017.

Dependent variable: municipal finances and population	Own-source revenues (log) (1)	Intergov. transfers (log) (2)	Total expenditures (log) (3)	Total debt outstanding (log) (4)	10-year default risk (pp) (5)	Population (log) (6)
Panel A. Poverty rate						
1 SD hurricane wind in last 1–10 years	-0.012***	0.006	-0.002	-0.033	-0.001	-0.005
	(0.004)	(0.012)	(0.004)	(0.020)	(0.000)	(0.004)
1 SD hurricane wind in last 1–10 years × 1 SD municipality poverty rate (1970)	-0.013*	0.013	-0.005	0.076	0.001***	-0.015*
	(0.007)	(0.013)	(0.006)	(0.050)	(0.000)	(0.009)
Panel B. Non-white population						
1 SD hurricane wind in last 1–10 years	-0.008**	0.009	0.001	-0.029	-0.000	-0.001
	(0.004)	(0.010)	(0.004)	(0.022)	(0.000)	(0.002)
1 SD hurricane wind in last 1–10 years × 1 SD pct. non-white population (1970)	-0.013**	-0.003	-0.009**	0.019	0.001**	-0.014
	(0.006)	(0.009)	(0.004)	(0.029)	(0.000)	(0.010)
Panel C. Less than high school						
1 SD hurricane wind in last 1–10 years	-0.016***	0.008	-0.004	-0.017	-0.000	-0.009
	(0.004)	(0.010)	(0.004)	(0.016)	(0.000)	(0.006)
1 SD hurricane wind in last 1–10 years × 1 SD pct. pop. without a high school degree (1970)	-0.008**	-0.002	-0.003	0.015	0.001***	-0.008
	(0.003)	(0.010)	(0.003)	(0.022)	(0.000)	(0.006)
Observations	49152	49152	49152	4067	9943	49152

Note: Outcomes are log revenues by funding source, log total expenditures, log total debt, 10-year default risk, and log population. Historical demographic attributes are de-meaned, and the interaction terms report hurricanes' additional impacts due to a one standard deviation increase in the attributes. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Standard errors are clustered at the county level.

Table B.5: Sensitivity Analysis of Trends in Municipal Government Revenues, 1982–2017.

Dependent variable: total revenues (log)	(1)	(2)	(3)	(4)
1 SD hurricane wind in last 1–5 years	-0.003	-0.002	-0.001	-0.004
	(0.005)	(0.005)	(0.007)	(0.004)
1 SD hurricane wind in last 6–10 years	-0.016***	-0.014*	-0.018**	-0.014*
	(0.005)	(0.008)	(0.007)	(0.008)
1 SD hurricane wind in next 0–4 years		0.007		
		(0.009)		
1 SD hurricane wind in next 0–9 years			-0.002	
			(0.006)	
Control for muni. linear time trends	N	N	N	Y
Observations	49152	43008	36864	49152

Note: Outcomes are log total revenues. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Standard errors are clustered at the county level. Column 2 controls for hurricane indices in t and $t+4$, Column 3 controls for hurricanes in t and $t+9$; Column 4 replaces municipality covarites with municipality-specific linear time trends.

Table B.6: Sensitivity Analysis of Trends in Municipal Government Expenditures, 1982–2017.

Dependent variable: total expenditures (log)	(1)	(2)	(3)	(4)
1 SD hurricane wind in last 1–5 years	0.005	0.004	0.003	0.004
	(0.004)	(0.005)	(0.006)	(0.004)
1 SD hurricane wind in last 6–10 years	-0.010*	-0.007*	-0.015***	-0.006
	(0.005)	(0.004)	(0.005)	(0.004)
1 SD hurricane wind in next 0–4 years		-0.003		
		(0.007)		
1 SD hurricane wind in next 0–9 years			-0.013**	
			(0.005)	
Control for muni. linear time trends	N	N	N	Y
Observations	49152	43008	36864	49152

Note: Outcomes are log total expenditures. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Standard errors are clustered at the county level. Column 2 controls for hurricane indices in t and $t+4$, Column 3 controls for hurricanes in t and $t+9$; Column 4 replaces municipality covarites with municipality-specific linear time trends.

Table B.7: Sensitivity Analysis of Trends in Municipal Government Debt, 1982–2017.

Dependent variable: total debt (log)	(1)	(2)	(3)	(4)
1 SD hurricane wind in last 1–5 years	-0.009	-0.006	-0.005	-0.009
	(0.022)	(0.022)	(0.021)	(0.018)
1 SD hurricane wind in last 6–10 years	-0.031*	-0.027	-0.035	-0.026
	(0.017)	(0.018)	(0.022)	(0.019)
1 SD hurricane wind in next 0–4 years		0.013		
		(0.013)		
1 SD hurricane wind in next 0–9 years			0.003	
			(0.012)	
Control for muni. linear time trends	N	N	N	Y
Observations	4067	4067	3486	4067

Note: Outcomes are log total debt outstanding. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Standard errors are clustered at the county level. Column 2 controls for hurricane indices in t and $t+4$, Column 3 controls for hurricanes in t and $t+9$; Column 4 replaces municipality covarites with municipality-specific linear time trends.

Table B.8: Sensitivity Analysis of Trends in Municipal Government Bond Rating, 1982–2017.

Dependent variable: 10-year default rate (pp)	(1)	(2)	(3)	(4)
1 SD hurricane wind in last 1–5 years	0.001**	0.001**	0.001**	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
1 SD hurricane wind in last 6–10 years	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
1 SD hurricane wind in next 0–4 years		-0.011		
		(0.012)		
1 SD hurricane wind in next 0–9 years			-0.005	
			(0.010)	
Control for muni. linear time trends	N	N	N	Y
Observations	9943	9939	9808	9943

Note: Outcomes are 10-year default rates. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects; as well as controls for mean bond characteristics (coupon rate, share of bonds that are general obligation, share of bonds sold at public auction, and maturity length). Standard errors are clustered at the county level. Column 2 controls for hurricane indices in t and $t+4$, Column 3 controls for hurricanes in t and $t+9$; Column 4 replaces municipality covarites with municipality-specific linear time trends.

Table B.9: Sensitivity Analysis of Hurricane Exposure Measurement, 1982–2017.

Dependent variable: revenues, expenditures, debt, and 10-year default rates	Hurricane exposure, non-linear in kt^3 (1)	Hurricane exposure, non-linear in kt^2 (2)	Hurricane exposure, non-linear in kt (3)	Maximum wind speed, kt^3 (4)	Maximum wind speed excl. Katrina, Rita, & Wilma, kt^3 (5)	Maximum wind speed $\geq$ 64 kts (=1) (6)	First hurricane exposure, non-linear in kt^3 (7)
Panel A. Total revenues (log)							
Impact 1–5 years	-0.003	-0.006	-0.005	-0.007	-0.006	-0.005*	0.002
	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Impact 6–10 years	-0.016***	-0.016***	-0.012***	-0.012**	-0.012**	-0.003	-0.006**
	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.004)	(0.002)
Panel B. Total expenditures (log)							
Impact 1–5 years	0.005	0.001	-0.001	-0.000	0.000	-0.001	0.006**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Impact 6–10 years	-0.010*	-0.013**	-0.011**	-0.010**	-0.010**	-0.003	-0.002*
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.003)	(0.001)
Panel C. Total debt (log)							
Impact 1–5 years	-0.010	-0.032	-0.044**	-0.036*	-0.028	-0.045**	0.001
	(0.025)	(0.026)	(0.019)	(0.022)	(0.021)	(0.019)	(0.007)
Impact 6–10 years	-0.035*	-0.050***	-0.055***	-0.051***	-0.047***	-0.051***	-0.012*
	(0.020)	(0.019)	(0.014)	(0.015)	(0.014)	(0.015)	(0.006)
Panel D. 10-year default rate (basis pt)							
Impact 1–5 years	0.066**	0.059*	0.017	0.031	0.004	-0.030	0.027***
	(0.025)	(0.030)	(0.026)	(0.024)	(0.021)	(0.023)	(0.008)
Impact 6–10 years	0.078***	0.064**	0.014	0.034	0.025	-0.031	0.039***
	(0.021)	(0.028)	(0.029)	(0.026)	(0.025)	(0.030)	(0.008)
Observations	49152	49152	49152	49152	49152	49152	49152

Note: Outcomes are log total revenues, log total expenditures, log total debt outstanding, and 10-year default rates (basis points). Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Panel D additionally controls for mean bond characteristics (coupon rate, share of bonds that are general obligation, share of bonds sold at public auction, and maturity length). Standard errors are clustered at the county level. The hurricane exposure measures in Columns 1 to 3 are based on non-linear functions of cubed, squared, and linear wind speed, respectively. The non-linear function is given by $\max(Wind_{it} - 50, 0)/MaxWind$, where $Wind_{it}$ is the maximum wind speed observed in municipality i and period t and $MaxWind$ is the maximum wind speed in the sample. The hurricane exposure measure in Column 4 is cubed maximum wind speed observed in the time period, adjusted by cubed maximum wind speed of the sample. The exposure measure in Column 5 is calculated in a similar fashion as Column 4, excluding Hurricanes Katrina, Rita, and Wilma. The exposure measure in Column 6 is whether the maximum wind speed experienced by a municipality exceeded 64 kts. In Column 7, the exposure measure is the hurricane exposure index associated with the first time a municipality experienced a hurricane strike between 1982 and 2007. In this specification, we also control for whether the first hurricane occurred over 10 years ago (relative to year t).

Table B.10: Sensitivity Analysis of the Estimated Fiscal Impacts of Hurricanes, 1982–2017

Dependent variable: revenues, expenditures, debt, and default rates	Total revenues (log) (1)	Total expenditures (log) (2)	Total debt (log) (3)	10-year default rate (pp) (4)
Panel A. Unweighted regressions				
1 SD hurricane wind in last 1–5 years	0.003	0.005	-0.045	0.001
	(0.007)	(0.007)	(0.027)	(0.000)
1 SD hurricane wind in last 6–10 years	-0.014	-0.014	0.015	0.000*
	(0.009)	(0.010)	(0.024)	(0.000)
Panel B. Nonimputed sample				
1 SD hurricane wind in last 1–5 years	-0.004	0.004	-0.010	0.001**
	(0.005)	(0.004)	(0.021)	(0.000)
1 SD hurricane wind in last 6–10 years	-0.015***	-0.010*	-0.031*	0.001***
	(0.005)	(0.006)	(0.018)	(0.000)
Panel C. Unbalanced sample				
1 SD hurricane wind in last 1–5 years	-0.003	0.005	-0.009	0.001**
	(0.005)	(0.004)	(0.022)	(0.000)
1 SD hurricane wind in last 6–10 years	-0.017***	-0.011**	-0.031*	0.001***
	(0.005)	(0.005)	(0.017)	(0.000)
Panel D. Dropping small cities				
1 SD hurricane wind in last 1–5 years	-0.006	0.004	-0.006	0.001**
	(0.005)	(0.004)	(0.021)	(0.000)
1 SD hurricane wind in last 6–10 years	-0.016***	-0.011*	-0.031*	0.001***
	(0.006)	(0.006)	(0.018)	(0.000)
Panel E. Moody's Sample				
1 SD hurricane wind in last 1–5 years	-0.008	0.005		
	(0.006)	(0.005)		
1 SD hurricane wind in last 6–10 years	-0.020**	-0.014**		
	(0.008)	(0.007)		
Panel F. Spatially clustered standard errors				
1 SD hurricane wind in last 1–5 years	-0.006	0.004	-0.006	0.001***
	(0.006)	(0.007)	(0.017)	(0.000)
1 SD hurricane wind in last 6–10 years	-0.016***	-0.011**	-0.031*	0.001***
	(0.006)	(0.006)	(0.017)	(0.000)

Note: Outcomes are log total revenues, log total expenditures, log total debt outstanding, and 10-year default rates. Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government fixed effects, and state-by-year fixed effects. Column (4) additionally includes controls for mean bond characteristics (coupon rate, share of bonds that are general obligation, share of bonds sold at public auction, and maturity length). Panel E column (3) and column (4) results for the Moody's Sample are shown in Table 4 columns (5) and (1), respectively. Standard errors are clustered at the county level except in Panel F, where errors are clustered spatially and spatial correlation is allowed up to 200 km.

Table B.11: Estimated Effects of Hurricanes under a Propensity Score Matching Approach, 1982–2017.

		Own-source revenues			Intergov. transfers		
Panel A. Dependent variable: revenues (log)	Total revenues (1)	Total own-source revenues (2)	Taxes (3)	Other revenues (4)	Total transfers (5)	Federal (6)	State & local (7)
1 SD hurricane wind in last 1–5 years	-0.029	-0.048	-0.039	-0.044	-0.018	0.045	-0.057
	(0.032)	(0.036)	(0.036)	(0.062)	(0.086)	(0.093)	(0.058)
1 SD hurricane wind in last 6–10 years	-0.059*	-0.063*	-0.066*	-0.069	-0.147**	-0.172	-0.050
	(0.032)	(0.036)	(0.036)	(0.049)	(0.069)	(0.112)	(0.061)
Observations	23496	23496	23496	23496	23496	23496	23496

	Expenditures					Debt	
Panel B. Dependent variable: expenditures & debt (log)	Total (1)	Public works (2)	Public safety (3)	Misc. (4)	Gov. admin. (5)	Total debt outstanding (6)	Long-term debt issued (7)
1 SD hurricane wind in last 1–5 years	-0.082**	-0.122**	-0.067	-0.038	-0.039	-0.154**	0.190
	(0.036)	(0.055)	(0.051)	(0.078)	(0.037)	(0.076)	(0.160)
1 SD hurricane wind in last 6–10 years	-0.068**	-0.046	-0.077*	-0.112*	-0.054*	-0.035	0.086
	(0.032)	(0.047)	(0.044)	(0.067)	(0.029)	(0.053)	(0.229)
Observations	23496	23496	23496	23496	23496	2751	2751

Panel C. Dependent variable: municipal bond ratings	10-year default risk (1)	Pct. bonds low risk (2)	Pct. bonds medium risk (3)	Pct. bonds high risk (4)
1 SD hurricane wind in last 1–5 years	0.001	-0.006	-0.007	0.013***
	(0.001)	(0.009)	(0.008)	(0.004)
1 SD hurricane wind in last 6–10 years	0.000	-0.026	0.022	0.004
	(0.000)	(0.018)	(0.014)	(0.006)
Observations	6959	6959	6959	6959

Note: Outcomes in Panels A and B are log revenues, expenditures, and debt, respectively. Outcomes in Panel C are implied municipal bond default risk and shares of bonds that are rated low risk (rated higher than "Baa)", medium risk (rated "Baa)", and high risk (rated lower than "Baa)". All specifications include fixed effects for the matched-propensity-score group and are weighted by the inverse difference in propensity score across control and treated municipalities within matched groups. (The propensity score for hurricane exposure between 1972 and 2017 is based on a logit regression with the following covariates: 1970 population, share of population with less than a high school degree, share of nonwhite population, poverty rate and the municipality land area and distance to a coast.) Additional controls include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), and state-by-year fixed effects. Panel C additionally controls for mean bond characteristics (coupon rate, share of bonds that are general obligation, share of bonds sold at public auction, and maturity length). Standard errors are clustered at the county level.

Table B.12: Effect of Hurricanes on Municipal Finances, Alternative Treatment Units, 1982–2017.

Dependent variable: public finances at different levels of geographies (log)	Revenues			Expenditures				
	Total revenues (1)	Own-source revenues (2)	Intergov. transfers (3)	Total expenditures (4)	Public works (5)	Public safety (6)	Public educ. (7)	Public assistance (8)
A. County-government type analysis								
1 SD in hurricane wind in last 1–5 years	-0.024***	-0.035***	0.009*	-0.024***	-0.005	0.003	0.001	-0.010
	(0.006)	(0.007)	(0.006)	(0.005)	(0.007)	(0.012)	(0.013)	(0.009)
1 SD in hurricane wind in last 6–10 years	-0.011	-0.019**	0.006	-0.010	-0.011	-0.011	0.013	-0.003
	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)	(0.012)	(0.018)	(0.011)
Observations	37914	37914	37914	37914	37914	37914	37914	37914
B. County-level analysis								
1 SD in hurricane wind in last 1–5 years	0.003	-0.002	0.013***	0.004	0.008	0.002	0.003	0.006
	(0.002)	(0.002)	(0.003)	(0.003)	(0.007)	(0.002)	(0.005)	(0.007)
1 SD in hurricane wind in last 6–10 years	0.000	-0.004*	0.010***	-0.002	-0.009**	-0.007*	-0.004	0.010
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)	(0.005)	(0.009)
Observations	10112	10112	10112	10112	10112	10112	10112	10112
C. State-level analysis								
1 SD in hurricane wind in last 1–5 years	0.004	0.001	0.009**	0.004	0.014***	0.004	0.000	0.003
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.011)	(0.003)	(0.005)
1 SD in hurricane wind in last 6–10 years	0.000	0.001	-0.001	-0.000	0.010**	0.007	-0.002	-0.001
	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)	(0.004)
Observations	756	756	756	756	756	756	756	756

Note: Outcomes are log revenues and expenditures. Panels A and B includes all governments (county, municipal, township, special-district, school-district governments) with non-missing total revenues and expenditures. Panel C reports state-level finances. The unit of observation in Panel A is county-government type-year and in Panel B is county-year. Baseline covariates include a vector of 1970 county characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area). Panel A controls for interactions between state fixed effects and government type-year dummies and interactions between baseline covariates and government type-year dummies. Panel B controls for baseline covariates interacted with year dummies and state-by-year fixed effects. Panel C controls for baseline covariates with state-specific linear time trends and census division-by-year fixed effects. Standard errors are clustered at the county level in Panels A and B and at the state level in Panel C.

Table B.13: Sensitivity Analysis of the Estimated Effects of Hurricanes on Municipal Bond Ratings, 1982–2017.

Dependent variable: municipal bond ratings (pp)	1-year default risk (1)	5-year default risk (2)	22-year default risk (3)	10-year default risk (4)	Pct. bonds low risk (5)	Pct. bonds medium risk (6)	Pct. bonds high risk (7)
1 SD hurricane wind in last 1–5 years	0.000	0.000*	0.001***	0.001***	-0.017	-0.001	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.008)	(0.004)
1 SD hurricane wind in last 6–10 years	0.000	0.000***	0.001***	0.001***	-0.062***	0.048***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.012)	(0.004)
Treatment unit	Muni. gov.	Muni. gov.	Muni. gov.	Bond	Bond	Bond	Bond
Observations	9943	9943	9943	176619	176619	176619	176619

Note: Outcomes are implied municipal bond default risk and shares of bonds that are rated low risk (rated higher than "Baa)", medium risk (rated "Baa)", and high risk (rated lower than "Baa)". Control variables include interactions of year dummies with a vector of 1970 municipality characteristics (share of population that are non-white, share of 25 and over population with no high school education, the poverty rate, log population, log distance to the nearest coast, and log land area), municipal government or debt instrument fixed effects, and state-by-year fixed effects. Columns 1 to 3 conduct the analysis at the the municipal government-level, control for mean bond characteristics (coupon rate, share of bonds that are general obligation, share of bonds sold at public auction, and maturity length), and are weighted by 1970 municipality population. Columns 4 to 7 conduct the analysis at the the debt instrument level, control for year dummies interacted with initial debt instrument characteristics (coupon rate, whether the debt instrument is general obligation, whether the debt instrument is sold at public auction, and maturity length), and are weighted by initial debt instrument sales amount. Standard errors are clustered at the county level.