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ABSTRACT

Since 1980, over 2,000 local governments in US Atlantic and Gulf states have been hit by a hurricane. Such natural disasters can exert severe budgetary pressure on local governments' ability to provide critical infrastructure, goods, and services. We study local government revenue, expenditure, and borrowing dynamics in the aftermath of hurricanes. These shocks impact, both, current local public resources through reducing tax revenues and expenditures, as well as future local public resources through increasing the cost of debt. Major hurricanes have much larger effects than minor hurricanes: major storms cause local revenues to fall by 6 to 7%. These losses persist at least ten years after a hurricane strike, leading to a 6% decline in expenditures on important public goods and services and a significant increase in the risk of default on municipal debt. Our results reveal how hurricanes can create a "vicious cycle" for local governments by increasing the cost of debt at critical moments after a hurricane strike, when localities are in greatest need of funding sources. Cities deemed riskier by ratings agencies face higher borrowing costs and thereby face constraints to invest in climate change adaptation. Municipalities with a racial minority composition above their state median suffer expenditure losses 9% greater and debt default risk 8 times larger than white communities in the decade following a hurricane strike. These results suggest that climate change can exacerbate environmental justice challenges.

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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 (see Figure 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 will examine 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. This gap in our understanding has important distributional consequences because local public services, such as transportation and public hospitals, are essential for lower income households (Glaeser et al., 2008) and because (as we document in this paper) local governments with large racial minority populations are more likely to be exposed to extreme weather events. Taken together, these facts highlight the important environmental justice implications associated with understanding who bears the cost of climatic natural disasters (Banzhaf et al., 2019).

We provide new evidence that exposure to hurricane events creates lasting declines in 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,[1] 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. For instance, 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). Second, local governments can generally rely on state reserve funds (Urahn and Irwin, 2020; Gregory, 2013)

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

and federally-backed insurance like FEMA to pay for damages to physical property in the aftermath 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, 2020). 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 negative effects of hurricane exposure on municipal budgets in the long run. We document that hurricanes can create a "vicious cycle" by increasing the cost of debt at critical moments after a hurricane strike, when localities are in greatest need of funding sources. In other words, we document that hurricane-induced declines in current financial resources translate in lower future investments, leading to further fiscal declines.

We use novel data on municipal bond default risk to show that higher borrowing costs and declines in outstanding debt are an important reason local governments are unable to recover pre-hurricane levels of service provision 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., 2019; 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 for the next year are made.

Our analysis provides two key findings. First, local governments experience significant declines in 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 ramp up 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 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 & local government employee payroll (Novy-Marx and Rauh, 2014).[2] Local revenue declines cause subsequent declines in local public goods provision: expenditures on 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

[2] 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).

exceeding 96 knots. The fact that expenditures decline nearly in tandem with revenues is consistent with prior work on local budgetary responses to local tax revenue shocks.[3]

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). We explore how debt financing and default risk change after a major shock. We find that 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 "near-miss" 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 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), Krueger et al. (2020), Painter (2020))[4]. Our paper is the first, to our knowledge, to combine granular hurricane exposure measures with local-level public finance outcomes. This exercise produces notably different conclusions from prior work because we show that local-level governments suffer losses following hurricane exposure. We show that aggregated county or state-level analyses mask these local negative impacts.

The second key finding is that we find greater losses of revenues and public goods expenditures among local governments that are, on average, poorer, less educated, and contain a higher population share of racial minorities. The magnitude implies that a one percentage point increase in the share of non-white population (measured as of 1970) exacerbates own-source revenue declines by 7.1% in the decade after a hurricane. Importantly, we find

[3]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).
[4]We discuss this literature in greater detail in Section 5.3

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 non-white or low-income households. 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, 2018; Groen et al., 2020).[5] No prior study, however, has explored demographic heterogeneity with respect to the impacts of hurricanes on local public resources. We find that declines in public goods provision comprise a channel by which climate change damages are 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.

Our results illuminate how disruptions in local provision of goods and services are an additional, yet heretofore undocumented, economic cost for those with the least ability to cope with natural disaster risk. Our analysis of the recent past is relevant for considering future risks likely to be posed by climate change as we show that fiscal costs are disproportionately borne by minority and lower-income communities.

This article proceeds as follows. Section 2 discusses the principle 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. Here, we consider mechanisms driving ratings agencies to adjust bond ratings, and distinguish between mechanical destruction to local economic conditions and updates to agency risk algorithms that account for climate change 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. This section also explores how population outflows and adjustments to the default risk for public debt play a role in local fiscal declines. Section 7 shows the results of

[5] In contrast, Billings et al. (2019) find that credit delinquency rates are higher after hurricane strikes among residents that are less likely to own homes relative to home owners.

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. We show evidence of this in Figure 2 where we plot the relationship between municipal debt and municipal bond ratings. For a one "notch" increase in bond rating rank (a higher risk bond) at time t, debt outstanding per capita falls by \$717 and debt issued per capita falls by \$120 at time $t + 5$, five years in the future. If a city's default rate 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 3 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 human capital as high-income residents 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 (Notowidigdo, 2020; 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.[6] 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.

[6]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.

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 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.[7] 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: data on local government finances, demographics, and hurricane exposure.

[7] 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.

3.1 Local Government Finance Data

First, 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 the Appendix.

In the Census of Governments dataset, local government revenues come from two main sources: locally-generated revenues and intergovernmental transfers. Locally-generated revenues generally come from taxes, with property taxes making up the largest category.[8] Additional own-source revenues ("other revenues" hereinafter) come from miscellaneous revenues and user charges and sources such as liquor stores and utilities. Intergovernmental transfers include funds from other governments, such as the federal, state, and other local governments. Public funds are allocated among a number of expenditure categories. We group the various expenditures into six categories.[9] We focus on the four largest expenditure shares: public works (48%), public safety (18%), miscellaneous expenditures (15%), and government administration (15%)[10].

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. As a robustness check, we adjust for municipality size by dividing public finance outcomes of interest by the municipality population. One caveat of using population-adjusted public finance outcomes is that these estimates are more prone to measurement error

[8]Other tax categories include sales taxes, income taxes, license taxes, and other miscellaneous taxes.
[9]The complete list of government expenditures can be found in Appendix A.
[10]We study the remaining two categories, public assistance (2%) and public education (2%) in the Appendix

because municipality population estimates are not updated frequently between decennial censuses. 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

Second, we collect data related to demographic and economic outcomes from several sources. To adjust for pre-hurricane differences in local characteristics, we collect data on municipalities' 1970 attributes from the National Historical Geographic Information System (NHGIS). 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, share of population that are 25 years and older and have less than a high school education, and poverty rate. Because these covariates are not available for many municipalities in 1970 (around 37% of the sample), we interpolate 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).[11] 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

Third, 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

[11] As a robustness check, we also re-estimate using a balanced panel of municipalities with non-interpolated 1970 controls. We show that our conclusions are not affected by using the smaller sample.

set contains the location (latitude and longitude) and wind speeds of storm events at six-hour intervals. We create hurricane tracks at 15-minute intervals by interpolating hurricane location and wind speeds between consecutive observations using a third-order polynomial.[12] Figure 4 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). 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. Appendix A contains the details of the measurement of hurricane exposure.[13] We prefer this continuous measure to alternative measures, such as a binary indicator for whether cities are struck by any hurricane, 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 wind speed, and cubed wind speed. Our preferred exposure measure abstracts from weighting by population exposed because using 2000 population weights can generate downward bias in the estimates as populations adjust to climate shocks over time.

3.4 Geographic & Demographic Variation in Hurricane Exposure

We plot the geographic distribution of aggregate hurricane exposure between 1972 and 2017 in Figure 5. Panel A shows that counties in coastal Louisiana, North Carolina, and Florida experienced 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.

[12] 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.

[13] Similar methods of measuring tropical cyclones' economic impacts have been used in the literature (Elliott et al., 2015; Mahajan and Yang, 2020).

Table 1 compares mean characteristics across municipalities exposed to any hurricane between 1972 and 2017 with those not exposed to a hurricane over this time period. We observe significant differences. Compared with non-hurricane municipalities, hurricane municipalities have larger revenues, larger expenditures on all service categories, and larger debt loads. Hurricane municipalities also have, historically, larger populations that are more educated with lower 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.[14] 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 rates (higher average bond ratings), possibly due to their larger tax revenues and population size. These cross-sectional differences in municipal characteristics underscore potential differences in trends, which we discuss and address in the next section.

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

[14] 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.

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. In some specifications, 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 $t-20$.

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. Municipality-specific fixed effects (α_i) account for the fact that localities more prone to hurricanes may have pre-existing disaster mitigation programs that reduce the effect of a hurricane. 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. We allow municipalities to exhibit differential trends according to a vector of initial characteristics measured as of 1970. These include 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, and standard errors are clustered at the county level.

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 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 "near-miss" design, where we utilize municipalities that barely miss exposure to major hurricanes as a comparison group. Our results suggest that ratings agencies downgrade bond ratings due to the negative economic shock caused by hurricanes; as opposed to re-assessment of the climate risk faced by local governments. 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 results in terms of standard deviation units of hurricane-strength wind speed for estimates of β_i in Equation 3—which is about 0.02 units of hurricane exposure—as well as heterogeneous treatment effects for major versus minor storms for estimates of δ_i and κ_i in Equation 4. To provide some intuition on the magnitude of a 0.02 increase in our index, we plot a histogram of the index in Figure 6 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.

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. All outcomes are in natural logarithms so that the coefficients represent percent changes.[15] In Panel A, the estimates in Columns 1 through 4 show that 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. These declines are driven primarily by the shortfalls in local tax revenues.[16] Other revenues (Column 3) 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

[15] Because there are zeroes in the 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 sufficiently larger than 1.

[16] Appendix Table B.1 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 subcategories are also negative, though less precisely estimated.

own-source revenues (Column 2) in the 6-10 years after exposure.

We estimate $\frac{dG}{dx}$ from Equation 2 in Column 5 of Panel A. Noticeably, hurricane exposure significantly increased 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, these findings suggest that institutions allowing for budget stabilization, like state rainy day funds (Knight and Levinson, 1999), are important for mitigating local fiscal distress.

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 municipalities exposed to major storms helps significantly to offset disruptions to local economic activity at least a year following exposure. Similar, our results reveal the potentially important role of the governmental transfers in smoothing municipal government spending in the aftermath of a natural disaster.

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 shortfall 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 $400,142 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 (which includes expenditures on worker compensation, insurance trusts, and interest on debt) are comparatively smaller in magnitude and imprecisely estimated. 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. Column (1) suggests that the average major hurricane reduces local government expenditures by 5.9% and public works expenditures by 13.7% in the 6-10 years after exposure.

In contrast to public works, government administration expenditures markedly 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.1 (Columns 5 through 7). Rather, it is most likely that these administrative spending increases are a result of increased spending on local disaster relief and use of "rainy day" funds. 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.

5.3 Local Debt Financing & the "Vicious Cycle" of Hurricanes

The prior sections established that hurricanes decrease *current* local government resources available to its residents. However, local governments generally rely on debt to finance the capital costs of long-term investments such as infrastructure, whereas tax revenues and fees pay for current operational costs. In this section, we show that hurricanes also hamper local governments' ability to finance *future* investments, leading to a vicious cycle.

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; Krueger et al., 2020). A growing, but relatively 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. Prior work on the implications of natural disasters for public finance focus on federal-level aggregates (Lis and Nickel, 2010; Noy and Nualsri, 2011; Melecky and Raddatz, 2011). Of these studies, 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. Our study also relates to recent work by Painter (2020) and Goldsmith-Pinkham et al. (2019). These papers utilize information shocks to show that municipal bond markets capitalize risk from anticipated sea level rise. The authors focus on the price of municipal debt in the "secondary market", e.g., the price of debt faced by end-of-market investors like individuals and investment funds. Our study complements this prior work in two ways. First, the Moody's data affords unique insight into how the supply-side, or the "primary market", of fixed income securities responds to climatic shocks. By combining the Moody's data with data on local public finances, we show that climate shocks reduce debt utilization through ratings agencies like Moody's. This channel is important to document because municipalities generally require debt to finance capital-intensive projects. Second, our approach relies on a panel fixed effect framework to compare outcomes before versus after hurricane strikes, thus informs the reaction of municipal bond markets to natural disaster shocks as opposed to anticipated sea level rise.

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 an indication of 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.[17] 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).[18] 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).

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 components of the bond yield, bond ratings specifically measure the probability of default. 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 vs revenue-backed, years to maturity, the size of the bond, and the baseline population size

[17] 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.

[18] 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 in the early 21st century 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).

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.

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).[19] 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 that cities that do not choose to be rated. This implies that hurricanes likely increase the 10-year default risk of un-rated municipal debt more than 0.1 percentage points documented here.

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 percentage points (Panel A, Column 3), equivalent to a 1.4% increase based on the sample standard deviation of the outcome.

[19]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.

Similarly, the share of bonds that are high risk increases by 1.4 to 1.6 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.

We take advantage of the bond data frequency to estimate default risk dynamics in the years leading up to and following hurricane exposure. Figure 7 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, *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 7 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. 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%. For a city like Philadelphia, which had 84 road and bridge projects under construction as of 2020, a 1% higher interest rate means that the city faces $13 million in added infrastructure costs for this year's projects alone.[20]

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. Columns 5 through 7 in Table 4 show estimates of how local government debt responds to hurricane exposure.[21] 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

[20] 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).

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

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 would imply this to be the case in the 6-10 years after a major hurricane. 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 or climate risk.[22] On the other hand, natural disasters can impact local public finance through raising out-migration, 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 routine fundamentals as opposed to hurricane exposure, itself, is important for projecting the future costs of climate change.

To this end, we proceed in two steps: we first assess how hurricanes impact local economic activity by focusing on changes to local population, employment, and home values. We, then, explore whether ratings agencies adjust their assessment of risk by comparing municipalities that barely miss exposure to a major storm to bordering towns that are hit. From the perspective of Moody's, these two types of locations shared similar ex ante exposure

[22] Goldsmith-Pinkham et al. (2019) finds, for instance, that the municipal bond market capitalizes climate change risk from sea level rise only after the IPCC 2013 report.

risk, and thus, 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 source county-level data on population and employment from the BEA, as well as county-level home values from Zillow.[23] 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 municipal-level in Column 1 and county-level population estimates 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). These magnitudes are similar to the population decline. 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. These dynamic effects are shown in Figure 8. Generally,

[23]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.

the annual-level partial effect estimates not only confirm the findings in Table 5 but also do not exhibit any pre-hurricane trends, suggesting that omitted trends are unlikely to be driving our local public finance results. Panel A shows a clear trend break in population: hurricane-exposed counties, on average, have higher population levels relative to their non-exposed counterparts in the years prior to hurricane strikes. Once exposed to hurricanes, the affected locations begin to lose residents, leaving population levels on par with their non-exposed, generally inland, counties. Panel B shows that employment falls below that of non-exposed county levels in the years following hurricane exposure. Panel C shows that home values fluctuate before hurricane strikes and begin to fall significantly by year four. Collectively, the evidence is consistent with the idea that ratings agencies downgrade municipal bond ratings because of economic decline and destabilization of the local tax base. Another potential explanation is that changes in bond ratings are due to increases in ratings agencies' assessment of climate risk in hurricane-exposed cities, which we examine below.

Changes in Moodys' Climate Risk Assessment? A "Near-Miss" Analysis

We check 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 miss exposure to the same storm event by chance.[24] Figure 9 plots coefficient estimates from this "Near Miss" analysis side-by-side with coefficient estimates from our main debt results in Table 4. The "Near Miss" estimates in Figure 9, 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.[25] 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. However, we report the "Near-Miss" estimates of the 1-5 year average

[24] 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 the municipality. If an adjacent county appears in multiple municipality groups, we use the largest union of these groups.

[25] 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 below and are available upon request. We prefer the current, less data-demanding approach because major hurricanes are infrequent events.

effect, and effects by storm intensity in tabular form in Appendix Table B.2. 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.

Instead, results of Figure 9 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 affected by a hurricane. Given the magnitudes of estimates from the "Near Miss" analysis are very similar to our main analysis, we conclude that ratings agencies do not take ex post climate risk into account when determining municipal bond default rates. Rather, post-hurricane increases in bond default risk are primarily a result of local tax revenue losses and local economic shocks.

Findings by Goldsmith-Pinkham et al. (2019) and Painter (2020) show that investors do 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 climate-specific risk does not impact bond default risk assessment in the primary "new issues" market differently than other non-climate related shocks.

6 The Environmental Justice Implications 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 environmental justice and climate risk. 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.

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 4 percentage point 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 face larger barriers to relocating to avoid environmental hazards or local economic shocks (Banzhaf and Walsh, 2008; Lin, 2019; Notowidigdo, 2020).

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. For ease of exposition, we 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 10 show that cities with a higher share of residents below the poverty line, non-white residents, and residents with no high school degree are significantly more harmed by hurricanes. The second row of each panel shows the heterogeneous treatment effects.[26] The coefficient estimate on revenues (colored in light blue) indicates that municipalities with one percentage point greater share of residents in poverty, that are non-white, or have less than a high school education experience, respectively, 9.8%, 7.1%, and 5.1% larger declines in own-source revenues as a result of a one standard deviation increase in hurricane wind speed. Expenditures fall more in these low socio-economic status (SES) municipalities, though the effect is precisely estimated only for historically non-white municipalities. The 10-year default risk increases significantly for low-SES municipalities as well, as shown by the red dots.Population declines appear to only manifest in low-SES municipalities (indicated in green). In fact, results of Figure 10 suggest that municipalities with no poverty, no racial minorities, and only highly-educated residents appear to suffer very little

[26]We report coefficient estimates of Figure 10 in tabular form in Appendix Table B.3.

changes to local government resources, expenditures, default risk, or population. If anything, these high-SES municipalities experience a *stimulus* in revenues and public goods provision, possibly due to an inflow of intergovernmental transfers, though these main effects (denoted in brown) are imprecisely estimated.

Overall, the findings demonstrate how hurricanes can cause a divergence in fiscal outcomes across municipalities that differ demographically, even within the same state. Our findings are consistent with recent work by Begley et al. (2020) who find applications for federal disaster-relief home loans are denied at higher rates in minority communities. To the extent that hurricane-induced fiscal shocks impact individual economic mobility, our results demonstrate that the spatial distribution of climate risk can contribute to structural 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, the sampled decades, alternative measures of hurricane exposure, or the level of government aggregation.

Persistence and pre-trends—Despite having shown pre-trend analyses of bond ratings and municipality characteristics, persistent effects of prior hurricanes as well as omitted trends may still confound our estimates of hurricanes' fiscal impacts. We take several steps to address these concerns. First, to check whether we are picking up the effects of historical hurricanes, we include additional 5-year lags and 10-year lags, which correspond to indicators for whether any hurricanes occurred between $t-15$ and $t-11$ and between $t-20$ and $t-11$, respectively. Second, to check whether our results are confounded by unobserved economic forces and differential growth paths of local economies, we perform a number of tests, including controlling for 5-year leads, 10-year leads, and municipal government-specific linear time trends. Appendix Table B.4 shows that our baseline estimate of the impact of hurricanes on local revenues is comparable to the estimates from these alternative specifications. We find that the magnitudes of the coefficients on the leads and lags are close to null and are are never statistically significant. Together, the findings suggest that differential local government growth paths are unlikely to drive our results.

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.5, we show that this intuitive measure yields similar conclusions as 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 any non-linearity in the damage function of hurricanes or if we exclude major hurricanes from 2005 (Katrina, Rita, and Wilma), which was a year that saw unusual hurricane activity, in measuring hurricane exposure.

Sensitivity to Empirical Specification—We show in Appendix Table B.6 that our main estimates are not sensitive to using alternative empirical specifications and approaches. 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. We believe this reflects the fact that larger local governments are better able to accurately track and report changes to their annual budgets. Our reason for weighting by population size is to reduce this source of measurement error. In Panel B, we measure fiscal outcomes in per capita terms and find similar results. Even after accounting for population outflows, own-source revenues (Column 2) and public works expenditures (Column 5) decline significantly per resident in the 6-10 years after hurricane exposure. Panel C shows restricting the analysis to the set of municipalities with non-interpolated 1970 covariates also does not change our conclusions. Finally, in Panel D, we show that using the full sample of municipal governments, as opposed to a balanced panel, renders similar conclusions to our main results.

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[27] and because they perform similar roles across US regions. In contrast, county governments, special districts, and townships can differ significantly in their provision of goods and services from region to another. In Appendix Table B.7 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.[28] 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.7, 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.[29] In Panel B, we also find evidence of revenue and expenditure declines among hurricane-exposed counties, though smaller than the estimates in Panel A for local governments, which indicates intergovernmental transfers likely occur between lo-

[27] 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.

[28] 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.

[29] 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.

cal 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.[30] Taken together, Appendix Table B.7 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.8 shows that the risk of default does not change for short-term debt instruments maturing in 1 or 5 years (Columns 1 and 5); but debt instruments that mature in 22 years have a similar increase in default risk as the 10-year debt instruments (Columns 2 and 4). 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. Decentralized public funding of goods and services can create immense budgetary pressure on local governments when they experience large, adverse shocks. Our results show that hurricanes cause locally-generated revenues

[30] 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.

as well as goods and services provision 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 initial fiscal impacts of hurricanes, but do not, on average, alleviate long-term declines in local government funding sources.

Our paper provides the first evidence that natural disasters can create a "vicious cycle" for local governments by increasing their cost of debt, 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 "viscous cycle" effect from major hurricanes documented here stands 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, Moody's does not appear to factor in climate shocks into its rankings. However, given that climate change will likely increase the frequency and severity of extreme weather events (Field et al., 2012; Emanuel, 2017), ratings agencies have an increased 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 will be more sensitive to climate shocks. Our study suggests that this market capitalization of climate risk will exacerbate spatial inequality because poor and minority communities are less resilient to climate-related shocks.

Is it socially efficient for capital to retreat from areas with greater climate risk? Noteably, most global economic activity is concentrated in coastal cities despite their vulnerability to natural disasters (Balboni, 2019). We leave it to future research to quantify the welfare implications of reallocating economic activity of public funds toward inland areas less exposed to climate-related shocks.

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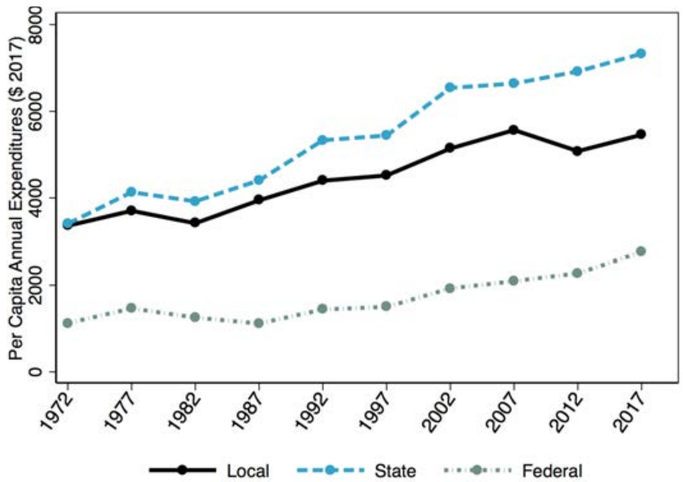


Figure 1: Public Goods Expenditures by Level of Government

Note: Figure plots per capita annual expenditures on public goods & services, including those related to 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. "Local" governments include municipalities, townships, school districts, special districts, and county governments.

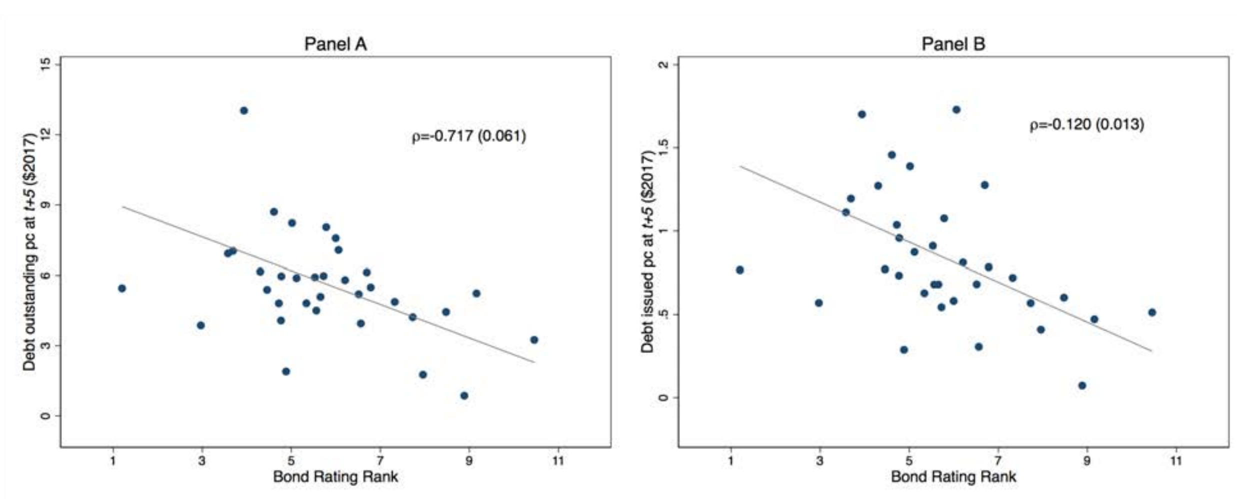


Figure 2: Relationship between Municipal Bond Ratings and Municipal Debt

Note: Panel A and Panel B plot the mean share of per capita debt outstanding and per capita debt issued, respectively, in year $t + 5$ for each of 40 bins of a municipality's average bond rating rank in year t. Each dot represents approximately 65 observations. All means residualized by state fixed effects and weighted by the 1980 local government population. ρ denotes the regression coefficient of debt outstanding per capita (Panel A) or debt issued per capita (Panel B) in year $t + 5$ as a function of bond rating rank in year t, controlling for state fixed effects and weighting by 1980 municipal population. Standard errors are in parentheses. Bonds with rating rank 1 have the lowest default risk ("AAA") whereas bonds rated 11 have the highest default risk ("Ba1"). Values in thousands of 2017 USD. Sample spans 1972 through 2017. Source: Census of Governments; Moody's Analytics.

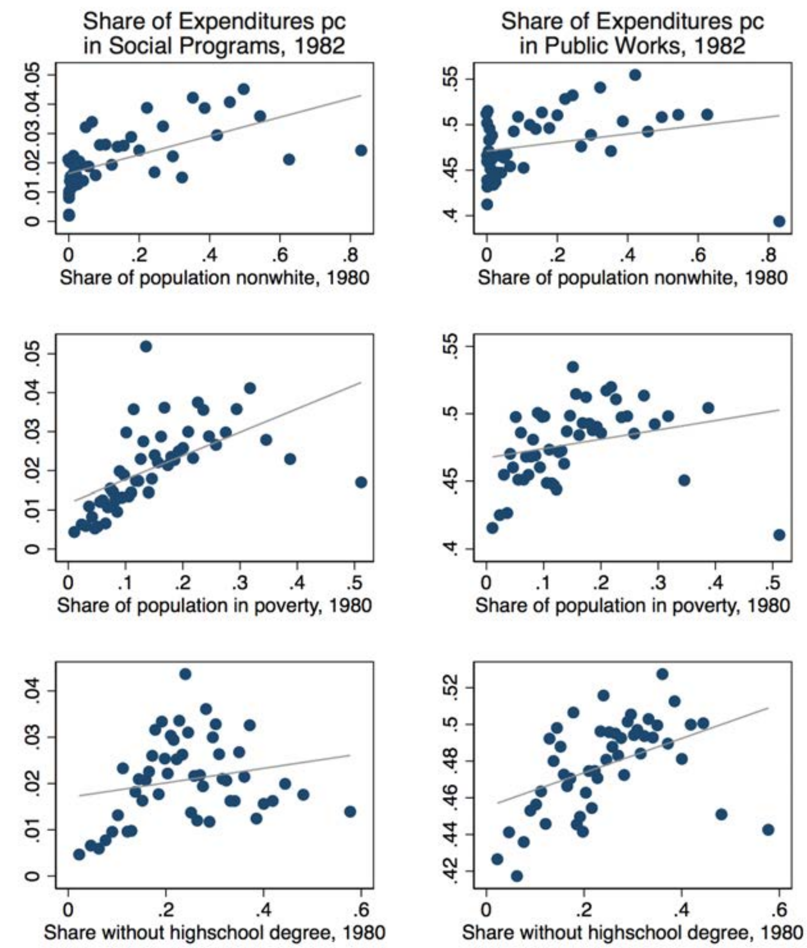
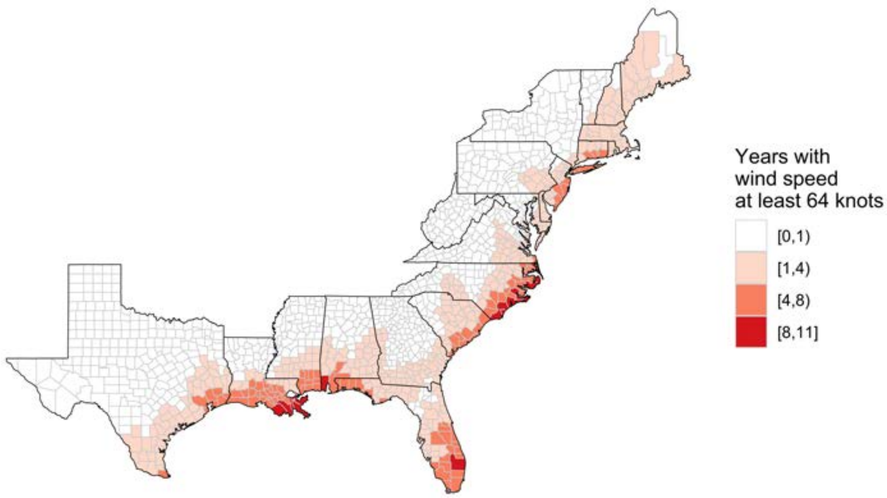


Figure 3: Provision of Local Public Goods & Demographic Composition

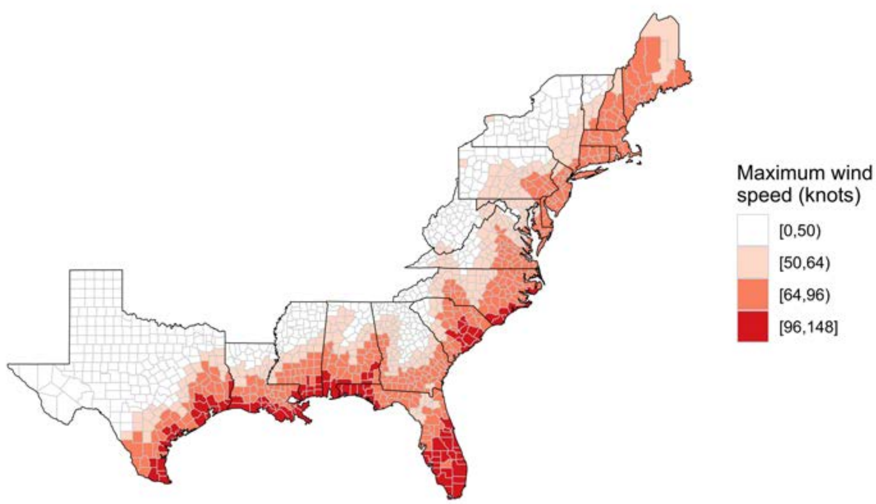
Note: Figure plots the mean share of per capita local government expenditures as of 1982 for each of 50 bins describing local demographic composition. Demographic characteristics measured as of 1980. Each dot represents approximately 130 general purpose governments. All means residualized by the 1980 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 4: 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 5: 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.

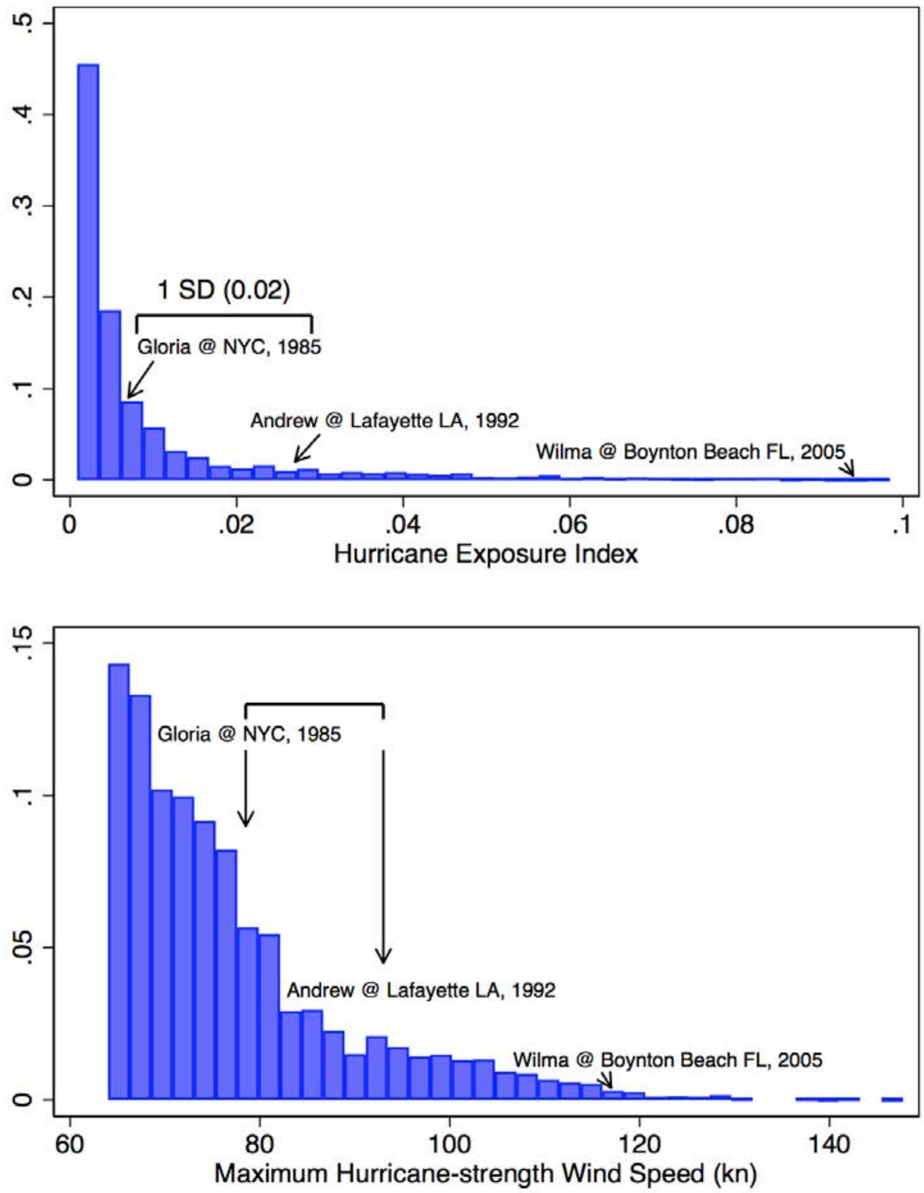


Figure 6: Distribution of Municipal Hurricane Exposure Index, 1972-2017

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.

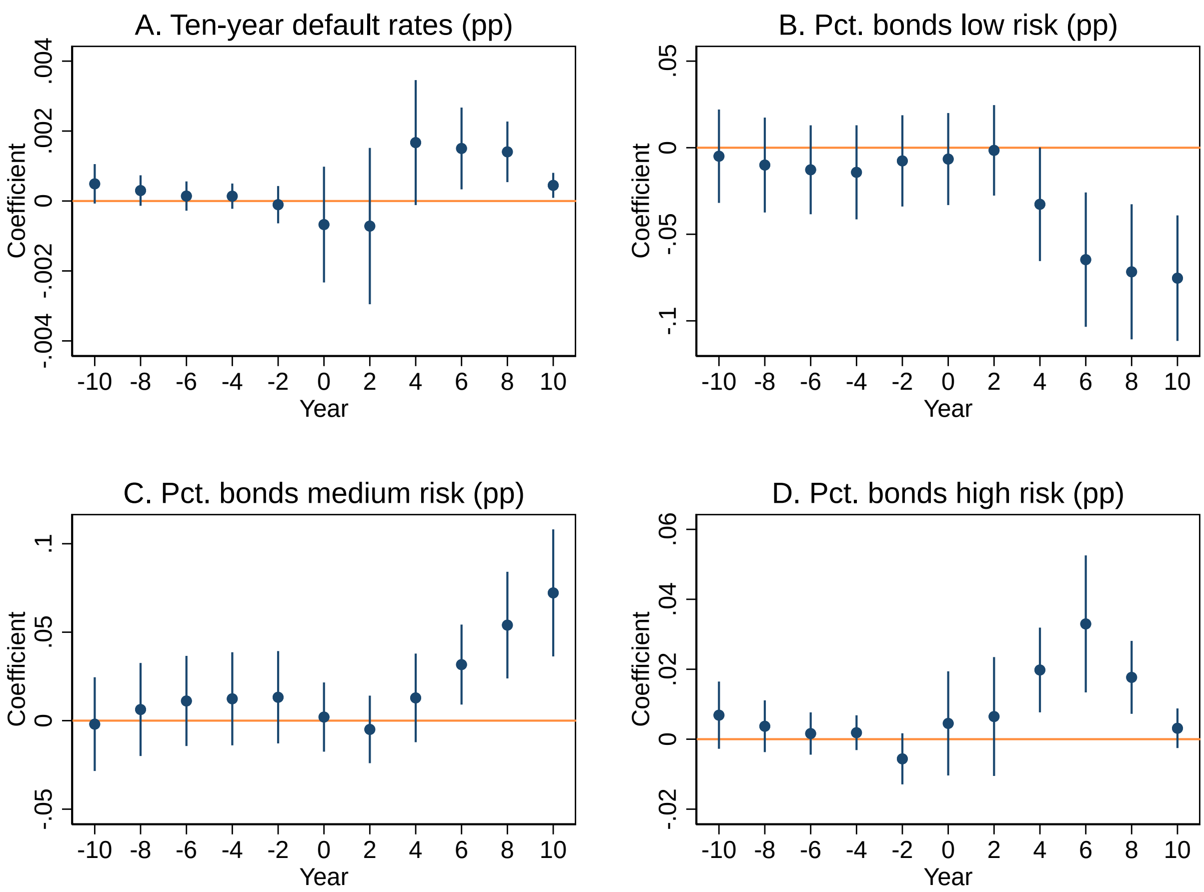


Figure 7: Hurricanes and Municipal Bond Rating Dynamics, 1982–2009

Note: Figure plots the estimates and 95% confidence intervals using Equation 5.

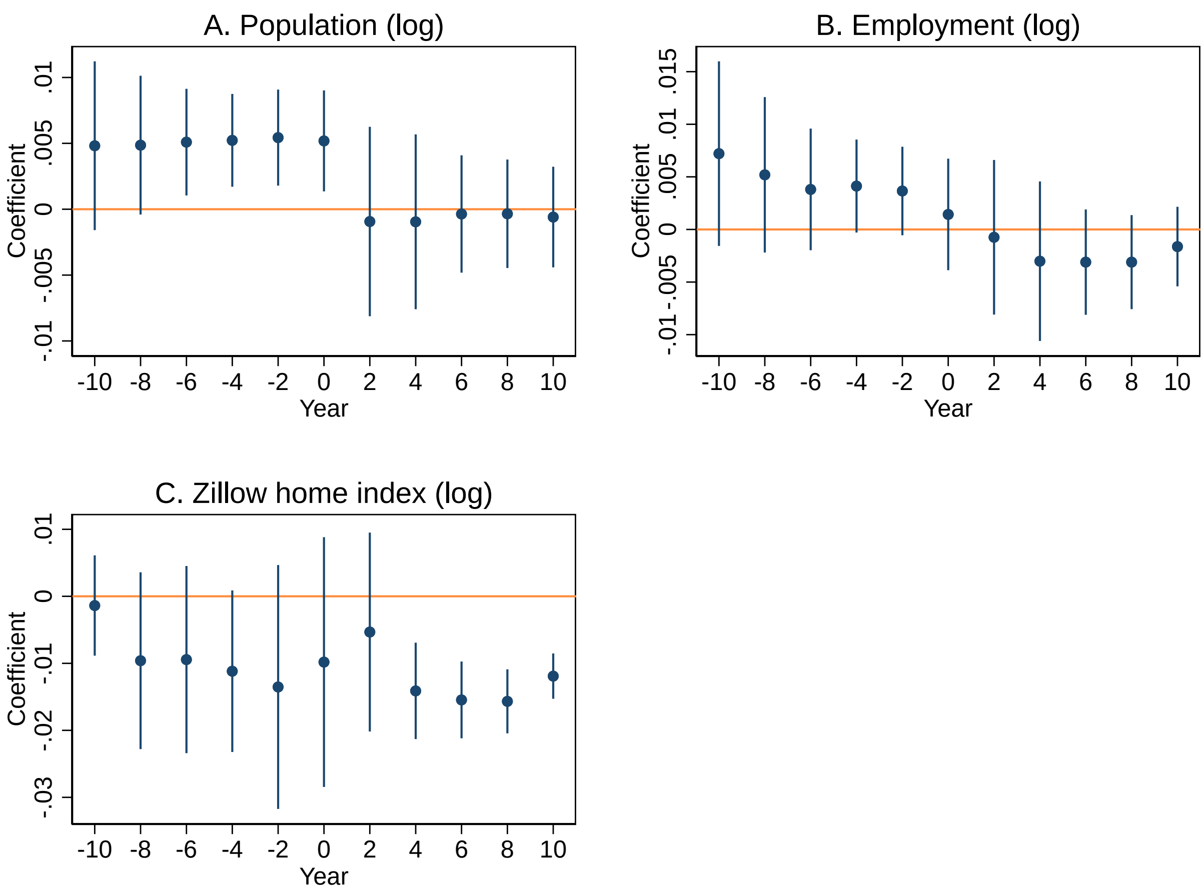


Figure 8: Hurricanes and County Population, Employment, and Home Value Dynamics, 1982–2009

Note: Figure plots the estimates and 95% confidence intervals using Equation 5.

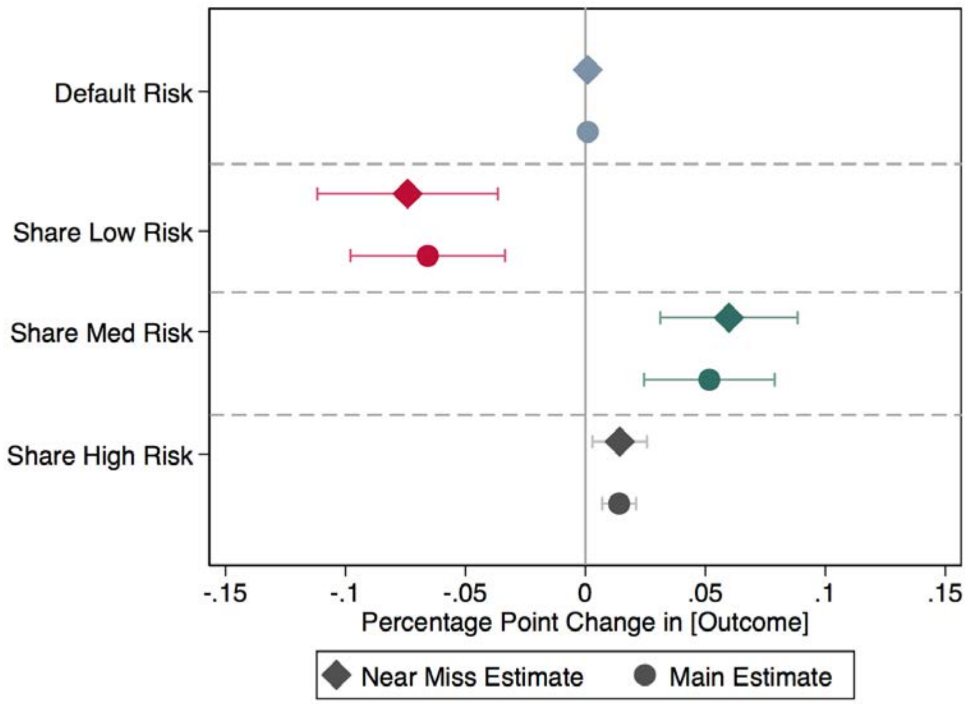


Figure 9: Near-Miss Analysis vs Main Analysis: Effect of Hurricanes on Municipal Debt

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 "Near Miss" analysis where we compare exposed municipalities to municipalities in bordering counties that were not exposed to the same storm. 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. Estimates on Default Risk are statistically significant at the 1% level.

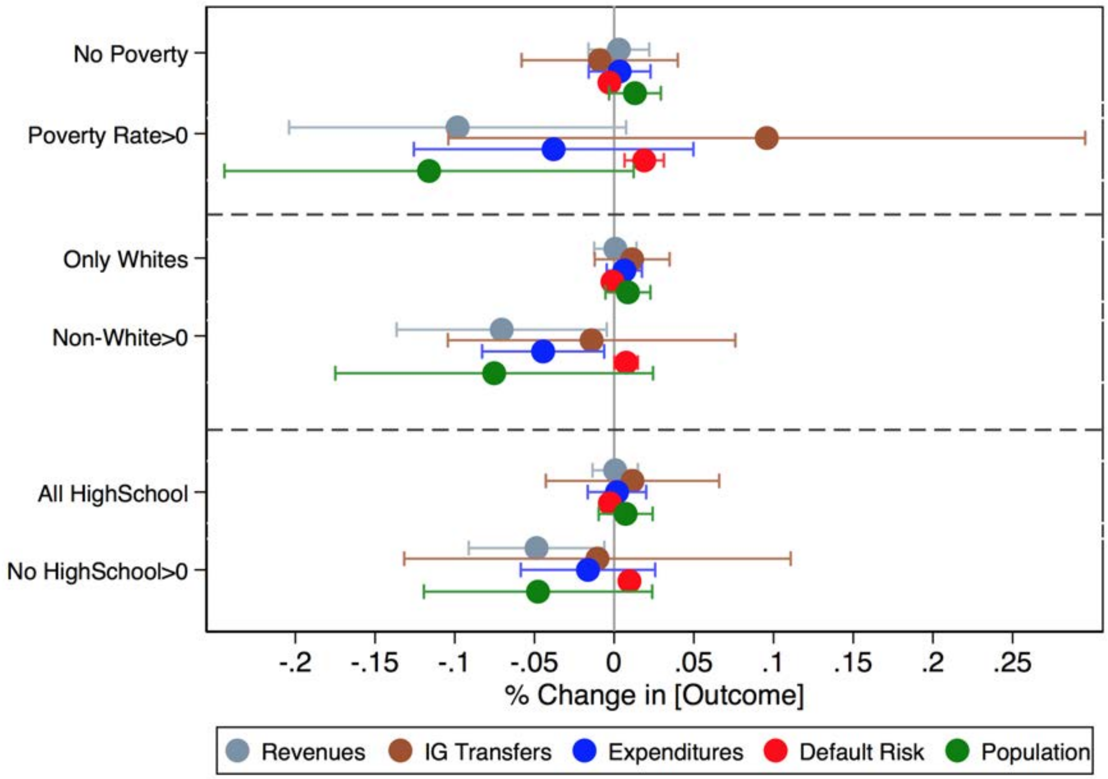


Figure 10: Fiscal Effects of Hurricanes by Demographic Attributes, 1982–2017

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 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). Estimates of κ_1 and κ_2 are estimated from one regression per demographic attribute. κ_1 measures the average annual change in outcome y in the 10 years after hurricane exposure for municipalities where $D_{i,1970} = 0$ and κ_2 measures the differential effect of hurricanes on outcome y for municipalities where $D_{i,1970} > 0$. 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	84.176	15.710	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	17.282	2.606	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.

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

		Own-source revenues			Intergov. transfers		
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)
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	0.003	0.025***
	(0.004)	(0.009)	(0.007)	(0.008)	(0.007)
1 SD hurricane wind in last 6–10 years	-0.010*	-0.034***	-0.005	-0.003	0.012*
	(0.005)	(0.007)	(0.008)	(0.016)	(0.006)
Panel B. Hurricane category					
Max wind speed $\geq$ 64 kts and $<$ 96 kts in last 1–5 years (=1)	-0.002	-0.008	0.013	-0.030	0.021
	(0.010)	(0.020)	(0.016)	(0.024)	(0.022)
Max wind speed $\geq$ 64 kts and $<$ 96 kts in last 6–10 years	-0.000	-0.024	-0.032	-0.033	-0.008
	(0.012)	(0.029)	(0.026)	(0.024)	(0.030)
Max wind speed $\geq$ 96 kts in last 1–5 years (=1)	-0.008	-0.062	0.030	0.019	0.100**
	(0.024)	(0.041)	(0.036)	(0.051)	(0.045)
Max wind speed $\geq$ 96 kts in last 6–10 years (=1)	-0.059**	-0.137***	-0.040	-0.094*	0.055
	(0.030)	(0.048)	(0.038)	(0.052)	(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. Standard errors are clustered at the county level.

Table 5: Effect of Hurricanes on Local Population Dynamics, 1982–2017.

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 ≥ 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 ≥ 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 ≥ 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 ≥ 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

Note: Outcomes are log municipality population, log county population, log county employment, and log Zillow county home value index. 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, and state-by-year fixed effects. 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. 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 centroid.[31] 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

[31] Storm tracks and wind speeds are estimated using Anderson et al. (2020). Their model accounts for surface friction using a reduction factor of 0.8 for points over land. We remove this surface friction component in the exposure measure by multiplying the estimated wind speeds by the reciprocal of 0.8.

zeros in the estimates. Third, 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: 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.2: Near-Miss 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	0.001	-0.024***	0.008	0.015***
	(0.001)	(0.009)	(0.007)	(0.005)))
1 SD hurricane wind in last 6–10 years	0.001***	-0.074***	0.060***	0.014**
	(0.000)	(0.019)	(0.015)	(0.006)
Panel B. Hurricane category				
Max wind speed $\geq$ 64 kts and < 96 kts in last 1–5 years (=1)	-0.002*	-0.022	0.067**	-0.045***
	(0.001)	(0.034)	(0.030)	(0.014)
Max wind speed $\geq$ 64 kts and < 96 kts in last 6–10 years (=1)	-0.002*	-0.020	0.064*	-0.044**
	(0.001)	(0.051)	(0.036)	(0.022)
Max wind speed $\geq$ 96 kts in last 1–5 years (=1)	0.009**	-0.185***	0.107***	0.078**
	(0.005)	(0.057)	(0.037)	(0.038)
Max wind speed $\geq$ 96 kts in last 6–10 years (=1)	0.004	-0.302*	0.244*	0.058
	(0.002)	(0.173)	(0.138)	(0.037)
Observations	10108	10108	10108	10108

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. Standard errors are clustered at the county level.

Table B.3: 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	0.003	-0.009	0.003	-0.121	-0.003***	0.013
	(0.010)	(0.025)	(0.010)	(0.074)	(0.001)	(0.008)
1 SD hurricane wind in last 1–10 years × 1970 municipality poverty rate	-0.098*	0.096	-0.038	0.578	0.019***	-0.116*
	(0.054)	(0.102)	(0.045)	(0.382)	(0.006)	(0.065)
Panel B. Non-white population						
1 SD hurricane wind in last 1–10 years	0.001	0.011	0.006	-0.042	-0.001	0.009
	(0.007)	(0.012)	(0.006)	(0.037)	(0.001)	(0.007)
1 SD hurricane wind in last 1–10 years × 1970 non-white population	-0.071**	-0.014	-0.045**	0.099	0.008**	-0.075
	(0.034)	(0.046)	(0.020)	(0.151)	(0.004)	(0.051)
Panel C. Less than high school						
1 SD hurricane wind in last 1–10 years	0.001	0.012	0.002	-0.048	-0.003***	0.007
	(0.007)	(0.028)	(0.009)	(0.052)	(0.001)	(0.009)
1 SD hurricane wind in last 1–10 years × 1970 pct. pop. without a high school degree	-0.049**	-0.010	-0.016	0.093	0.010***	-0.048
	(0.022)	(0.062)	(0.021)	(0.139)	(0.002)	(0.037)
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. 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.4: Sensitivity Analysis to Persistent Hurricane Effects and Pre-Trends, 1982–2017.

Dependent variable: total revenues (log)	Baseline (1)	11 to 15-year lags (2)	11 to 20-year lags (3)	0–4-year leads (4)	0–9-year leads (5)	Muni. gov. time trends (6)
1 SD hurricane wind in last 1–5 years	-0.003	0.001	-0.003	-0.002	-0.001	-0.004
	(0.005)	(0.005)	(0.007)	(0.005)	(0.007)	(0.004)
1 SD hurricane wind in last 6–10 years	-0.016***	-0.014**	-0.013*	-0.014*	-0.018**	-0.014*
	(0.005)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
1 SD hurricane wind in last 11–15 years		0.003				
		(0.004)				
1 SD hurricane wind in last 11–20 years			0.000			
			(0.004)			
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)	
Observations	49152	43008	36864	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 $t-11$ and $t-15$; Column 3 controls for hurricane indices in $t-11$ and $t-20$; Column 4 controls for hurricane indices in t and $t+4$, Column 5 controls for hurricanes in t and $t+9$; Column 6 replaces municipality covarites with municipality-specific linear time trends.

Table B.5: Sensitivity Analysis of Hurricane Exposure Measurement, 1982–2017.

Dependent variable: total revenues (log)	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)
Impact 1–5 years	-0.003	-0.006	-0.005	-0.007	-0.006
	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)
Impact 6–10 years	-0.016***	-0.016***	-0.012***	-0.012**	-0.012**
	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)
Observations	49152	49152	49152	49152	49152

Note: Outcome is 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. 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 cubed 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.

Table B.6: Sensitivity Analysis of the Estimated Fiscal Impacts of Hurricanes, 1982–2017.

Dependent variable: revenues and expenditures (log)	Revenues			Expenditures		
	Total revenues (1)	Own-source revenues (2)	Intergov. transfers (3)	Total expenditures (4)	Public works exp. (5)	Public safety exp. (6)
Panel A. Unweighted regressions						
1 SD hurricane wind in last 1–5 years	0.005	-0.008	0.040**	0.006	0.000	-0.007
	(0.007)	(0.006)	(0.018)	(0.007)	(0.010)	(0.015)
1 SD hurricane wind in last 6–10 years	-0.009	-0.014*	-0.019	-0.010	-0.012	-0.014
	(0.009)	(0.008)	(0.020)	(0.010)	(0.014)	(0.018)
Panel B. Per-capita finances						
1 SD hurricane wind in last 1–5 years	0.005	0.001	0.031**	0.013***	0.007	0.016*
	(0.005)	(0.005)	(0.013)	(0.005)	(0.006)	(0.009)
1 SD hurricane wind in last 6–10 years	-0.009	-0.013**	0.002	-0.003	-0.026***	0.001
	(0.007)	(0.007)	(0.014)	(0.006)	(0.008)	(0.008)
Panel C. Nonimputed sample						
1 SD hurricane wind in last 1–5 years	-0.004	-0.008	0.025**	0.004	-0.003	0.010
	(0.005)	(0.006)	(0.011)	(0.004)	(0.009)	(0.007)
1 SD hurricane wind in last 6–10 years	-0.015***	-0.019***	-0.002	-0.010*	-0.034***	-0.004
	(0.005)	(0.006)	(0.016)	(0.006)	(0.007)	(0.008)
Panel D. Unbalanced sample						
1 SD hurricane wind in last 1–5 years	-0.003	-0.008	0.024**	0.005	-0.003	0.007
	(0.005)	(0.006)	(0.011)	(0.004)	(0.009)	(0.006)
1 SD hurricane wind in last 6–10 years	-0.017***	-0.022***	-0.005	-0.011**	-0.037***	-0.008
	(0.005)	(0.005)	(0.015)	(0.006)	(0.007)	(0.006)

Note: $N = 49,152$ except for Panel C ($N = 18,512$), and Panel D ($N = 51,497$). Outcomes are log revenues (total and by funding source) and expenditures (total and the two largest spending categories). 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. Standard errors are clustered at the county level.

Table B.7: 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.8: 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 rates 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.