Federal Disaster Relief and Moral Hazard: The Case of Local Government Infrastructure Investments

Kendra Marcoux*

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Abstract

This paper aims to quantify the way that the FEMA Public Assistance Program distorts local government investments in public infrastructure adaptation and maintenance within their districts. I find that counties that receive federal insurance funding spend less on highways and general infrastructure projects in both the year of, and the year following, a disaster when compared to counties that did not receive funding but experienced similar levels of per capita damages. This result indicates that municipalities that receive insurance payouts may be less willing to invest in decreasing local exposure to climate risk than counties that were forced to shoulder the costs of disaster repairs themselves.

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1 Introduction

Between 2010 and 2019 the Federal Emergency Management Agency's (FEMA) Disaster Relief Fund (DRF) had a total budget of over 145 billion real USD.[1] Over 55% of that budget was directed towards the Public Assistance Fund, which aids state and local governments in financing the repairs to public goods following severe natural disasters.[2] Moreover, the aggregate size of the DRF budget increased over 280% between the periods of 1980 to 1999 and 2000 to 2019, and as the effects of climate change continue to grow, the frequency of natural disasters will only increase, thus further expanding the size of this transfer from the federal to state and local governments.

While the federal government covers the cost of necessary repairs to public goods following large disasters, the cost of climate adaptation to, and regular maintenance of, public goods often falls on local governments. If municipalities believe that the federal government will shoulder the costs of either climate adaptation or regularly scheduled public infrastructure maintenance in the year of, or following, a natural disaster as a part of FEMA funded repairs, they may face a disincentive to budget for these costs ex ante. The federal government cannot to credibly commit to withholding Public Assistance funding following a disaster, which may encourage local governments to forgo climate adaptation or normal infrastructure maintenance and instead rely on federal funds to pick up these costs as a part of post-disaster repairs.

An important feature of FEMA Public Assistance funding, however, is that it is only available to those state and local governments which have suffered sufficient per capita damages from a disaster. This condition means that every year a number of states experience

[1] In 2020 and 2021, the FEMA DRF covered COVID-19 relief which renders spending in those years misrepresentative.

[2] The other programs that covered by the DRF include Individual Assistance, which accounts for around 15% of the budget and aids households in the repairs to uninsured private property, the Hazard Mitigation Program, which accounts for 7% of the total budget and provides climate adaptation grants to public property, and general administration and operations costs. (*The Disaster Relief Fund: Overview and Issues*, 2022)

disasters which cause per capita damages levels that fall just short of the federally determined threshold. These municipalities suffer damages levels that are similar to areas that do receive federal insurance, but their expenditure decisions are not impacted by the promise of federal aid.

This paper applies a fuzzy regression discontinuity design (FRD) to analyze how the incidence of receiving federal funding after a severe weather event impacts the way that local governments make public infrastructure expenditure decisions. The intent of the FRD design is to estimate the causal effect of receiving FEMA funding on municipality budget allocations for climate adaptation and maintenance following a costly disaster. I leverage publicly available data on the Preliminary Damages Assessments (PDA) that are run jointly between states and FEMA, and use these federally assessed per capita damages figures as the running variable in a FRD design. I then take data from the Annual Survey of State and Local Government Finances to determine how spending decisions of municipalities who received aid differ from the budgets of those with comparable levels of damages but which did not receive funding.

I find that counties that receive federal funding following a disaster do, on average, exhibit lower direct expenditure on general infrastructure, highways, and fire protection, and have lower levels of total debt outstanding in both the year of, and the year following, a Public Assistance application than counties who do not receive funding and which have similar levels of damages. These results, which are precisely estimated for both infrastructure and highway expenditures in the year following a disaster, suggest that moral hazard resulting from FEMA Public Assistance grants may in fact distort the way that municipalities choose to invest in public infrastructure.

The use of a FRD design implies that my results can only estimate the local average treatment effect of FEMA funding, which will only signify a causal relationship between receiving funding and expenditure decisions for municipalities that experience disaster-caused damages that fall within a certain range (Imbens & Angrist, 1994). I argue that these results are nonetheless crucial to understand due to the fact that the vast majority of natural disasters are less costly events which cause damages that approach the threshold as opposed to Hurricane Katrina-sized storms. Further, the average estimate of Public Assistance funding for disasters that fall within my largest bandwidth is $15.4 million, meaning these disasters still represent a large transfer between the federal and state and local governments.

This study adds to the growing literature on natural disaster aid (Garrett & Sobel, 2003; Kousky, Luttmer, & Zeckhauser, 2006; Cohen & Werker, 2008; Deryugina, 2017; Davlasheridze, Fisher-Vanden, & Klaiber, 2017; Baylis & Boomhower, 2019; Fried, 2021), and to the robust literature on moral hazard (Arrow, 1951; Arrow, 1963; Pauly, 1968; Marshall, 1976; etc). Much of the existing literature on the role of moral hazard in natural disaster insurance markets, however, focuses on the moral hazard on behalf of households and private actors rather than local governments.[3] Furthermore, the majority of the literature surrounding natural disasters in general focuses on catastrophic disasters such as Hurricanes Katrina or Harvey, rather than lower cost disasters which fall within a bandwidth of the FEMA damages threshold. This study contributes to the current natural disaster literature by focusing not only on more frequent, lower cost disasters, but also on the way that FEMA Public Assistance bailouts might distort state and local investment decisions. To the best of my knowledge this study is the first to analyze the incidence of receiving aid following disasters that fell just above the federal damages threshold rather than major disasters.

The paper proceeds as follows: Section 2 provides a background on the history of FEMA and the Public Assistance Fund and a discussion on why the growing risk caused by climate change makes the question of moral hazard in this context more important than ever. Section 3 describes the data. Section 4 outlines the empirical strategy. Section 5 presents the results of the model. Section 6 offers a discussion of the results and possible explanations. Section

[3]Exceptions include Raschky and Schwindt (2016) which studies the effect that foreign aid to developing countries has on natural disaster preparedness, Baylis and Boomhower (2019) which focuses on the effect that federal and state fire protection transfers have on local government zoning and building code decisions, and Fried (2021) which develops a macroeconomic model to quantify the effects that federal disaster policies have on adaptation capital and climate change.

7 concludes.

2 Background

When a natural disaster occurs the costs are covered first by local and state governments. If a state governor finds that a recent event has caused damages that exceed the capacity of both state and local municipalities, and that supplemental federal assistance is necessary to save lives, protect property or public health and safety, or to lessen the threat of the disaster, he or she can apply for a grant from the FEMA Public Assistance Fund.[4] Some disasters, such as Hurricanes Katrina or Harvey, cause apparent catastrophic damages which clearly exceed the federal statewide per capita damages threshold without need for further assessment. However, for smaller, edge case disasters FEMA will initiate a PDA which will be performed jointly between FEMA and the state. As a part of this process, state officials will send photos of the damages and further documentation to FEMA officials who will ultimately decide the level of state and county-wide per capita damages caused by the respective event. Figure 1 shows a map of the federally assessed per capita damages levels in counties that were listed in Public Assistance funding applications in 2015.

Following the completion of the PDA, each gubernatorial application is then reviewed by the contemporary US President who has the ultimate decision to grant a Presidential Disaster Declaration (PDD) and allow the impacted counties access to Public Assistance funds. In this case, FEMA acts as an insurer for the costs of clean up and rebuilding public goods following a disaster.

For disasters that qualify for a damages assessment, PDAs assess per capita damages levels for both the counties originally listed as being impacted by the respective state governor and for the entire state. Although FEMA sets per capita damages thresholds for both state

[4] Only around 1.5% of the severe weather events that were classified as having positive damages levels in the National Oceanic and Atmosphere Administration (NOAA) Storm Events Database applied for Public Assistance funding from FEMA.

and county level damages, the decision to extend a PDD to an application often revolves around the proximity of the statewide per capita damages to the statewide threshold rather than the analogous county level figures.[5] This means that geographically compact disasters in high-population states are less likely to receive funding than similar sized disasters in less populous states, mainly due to the fact that FEMA judges funding needs based off of the capacity and budget of the respective state government, and not the local severity.[6] It should be noted that as this decision is subjective, the damages threshold is not the only relevant factor in the allocation of insurance funding.

2.1 Potential Market Failures

In the case of natural disaster insurance for state and local governments, the first best insurance policy would equalize the marginal utility of a dollar in the government budget in non-disaster periods to the marginal utility of a dollar in the government budget after a disaster occurs. The problem of moral hazard arises, however, when the actions of the federal government create adverse incentive effects, and when the federal government cannot commit to withholding insurance payments (Rodrik & Zeckhauser, 1988). The federal government's inability to commit to non-intervention may induce local governments to exert less effort in reducing their exposure to natural disaster risk.[7] Moral hazard creates a market distortion which prevents the first-best insurance contract from being implemented.

Federal disaster aid to independent municipalities may lead to at least two different sources of possible distortions: the first is the spatial location of new public infrastructure

[5] This fact means that it is not uncommon for a state governor to be denied Public Assistance funding following a PDA that found per capita damages which fell above the county-level threshold in a series of counties, but which also found that state-level damages fell below the statewide threshold.

[6] Occasionally if the state per capita damages exceed the threshold but certain counties that the state governor included in his or her aid application fall below the county threshold, FEMA will advise that funds not be used for repairs in those counties. The final decision on funds allocation is at the discretion of the state government.

[7] Moral Hazard is most traditionally examined within the context of healthcare insurance, dating back to Arrow (1963). In the healthcare insurance literature, they refer to this type of moral hazard, in which insurance creates a disincentive for individuals to maintain their health, as "ex ante moral hazard" (Einav & Finkelstein, 2018).

construction while the second is the maintenance and climate adaptation of existing public goods. If state and local municipalities believe that FEMA will finance the repairs to public infrastructure in the case of a natural disaster, they may be less incentivized to limit new public infrastructure construction to low risk areas within their districts or to regularly invest in the upkeep of existing public goods, thus exacerbating the cost of destruction from disasters.

State and local authorities historically shoulder the majority of the burden in investing and maintaining public infrastructure within their municipalities.[8] Furthermore, there is a crucial need for an improvement in the physical condition of American infrastructure. Every four years the American Society of Civil Engineers (ASCE) examines the current conditions and needs of 17 different categories of US infrastructure,[9] and offers a grade in a simple A to F school report card format to summarise the state of the nation's public infrastructure. In 2021, the ASCE scored overall US infrastructure at a C-, with roads and public transit scoring a D and D-, respectively. ASCE estimates that by 2039, a continued underinvestment in public infrastructure will cost over $10 trillion in lost GDP, and the increasing frequency and severity of natural disasters will only increase that cost. As temperatures and precipitation levels rise in the United States, much of the existing American infrastructure that meets current engineering standards will degrade at a faster rate.

Furthermore, as a result of both the increasing frequency of extreme weather events and the Covid-19 pandemic, the federal government is currently directing a historically high portion of its budget towards disaster relief.[10] As such, FEMA is hoping to raise its statewide per capita damages indicator such that state and local governments will shoulder more of the

[8] In 2017 the federal government spent $65 billion on physical capital for transportation capital including highways, mass transit, rail, water, and air. In that same year state and local governments invest $72 billion for the same purposes. Over the period of 1962 to 2017 the gap between federal and state and local investment in transportation infrastructure has been widening. (Congressional Budget Office, 2019).

[9] These categories include bridges, dams, drinking water, energy, public parks, rail, and wastewater among others (ASCE, 2021).

[10] With the exception of the relief directed towards Hurricane Katrina in 2005, the annual DRF appropriations in 2020 and 2021 are the two highest in FEMA history. Further, FEMA's rolling four year average budget hit a record high between 2016 and 2020 and then again between 2017 and 2021.

economic burden of natural disasters in the future.[11] These facts underscore the importance of understanding the mechanisms that determine local infrastructure expenditure decisions and in turn how that localities reduce their exposure to climate risk.

3 Data Description

To assess the impact that receiving Public Assistance funding has on municipality-level spending, I constructed a novel dataset by merging together data from a number of different sources. I began by performing a one-to-many merge between data from FEMA PDA assessments, which list out a number of impacted counties on each application, and expenditure data from the Annual Survey of State and Local Government Finances, which lists local governments and their respective county codes. My final dataset is at the county and independent municipality ID name level (as listed in the Annual Survey of State and Local Government Finances) and contains a row for each disaster application the respective ID name's county code was included on. I also join on data for other federal grants that certain counties receive or get approval for in a given year and I leverage data from the Inter-University Consortium for Political and Social Research (ICPSR) at the University of Michigan on gubernatorial political affiliations to control for the political party of the governor who submitted each application.[12]

The final data set is limited to a bandwidth equal to the statewide per capita damages threshold for each observation and contains 14,027 independent municipalities who were included in FEMA Public Assistance applications in a given year, associated with 350 distinct applications. Table 1a gives summary statistics on the statewide damages of the disasters that remain in the sample, and Table 1b gives a summary of descriptive statistics of the

[11] In December 2020, FEMA proposed an increase in the statewide per capita indicator from \$1.50 to \$2.32, which would lead to around a 27% decrease in the number of Public Assistance grants offered to state and local governments. If this policy, adjusting for inflation, had been implemented between 2008 and 2017 it would have reduced total federal aid by \$2.1 billion. (FEMA, 2020).

[12] Garrett and Sobel (2003) find gubernatorial aid applications are more likely to be approved if the respective governor is a member of the same political party as the contemporary US president.

main expenditure categories of in both the year of and the year following a Public Assistance application.

3.1 FEMA Preliminary Damages Assessments

I first assembled a dataset on the PDA estimates for every gubernatorial application for FEMA aid following a natural disaster between the period of Q4 2007 and Q4 2021. These PDA results are publicly available in the form of PDF reports posted by FEMA in response to an application during the time period. I was able to scrape these PDFs to attain data on the impacted counties,[13] county and state level damage figures, disaster types, the main source of public damages, the name of the governor who applied for funding, and the final status of funding approval. This dataset includes FEMA's responses to over 1,050 funding applications coming from all 50 states and the District of Columbia, and referencing 1,735 distinct impacted counties and Native American Reservations. The counties listed in these PDFs are listed by name only, so I cleaned the names and joined them to FIPS codes using string matching.

3.2 County Level Finances

These data include a complete census of county and municipality level spending for each county in the country on years ending in 2 and 7, and include county-level surveys and estimates during non-census years.[14] I have these data for years 2007-2019. I have included the finances for not only every independent-governing county in the that applied for natural disaster funding from FEMA but also for the independent municipalities that are contained

[13]For applications that are eventually approved, it is sometimes the case that the list of impacted counties does not match the list of counties that eventually receive Public Assistance Funding. For funding applications that were denied, on the other hand, the only source of affected counties available from FEMA is the list provided in the original application. I have chosen to limit the counties in my final dataset to those which were listed in the original application for Public Assistance Funding such that I treat disasters the same way if they were approved for funding or not.

[14]During survey years the population of US counties and independent governing municipalities is not complete.

within them.

3.3 FEMA Public Assistance and Hazard Mitigation Grants

For those natural disasters that received aid following a gubernatorial request, I control for the per capita level of aid that each county and local municipality received from past disasters in a given fiscal year. For Public Assistance funding that was directed to an entire state rather than a county, I assigned a population-weighted share of the total funding to each county in the state. For the independent municipalities within each county I also assigned a population weighted share of the county level funding from each PA grant.

FEMA also provides data on the federal aid granted to state governments for the purpose of hazard mitigation. I control for the level federal hazard mitigation grants that each county got approval for in a given year. I assign county and independent municipality level funding using the same weights as in the Public Assistance grants.

4 Empirical Strategy

FEMA directs Public Assistance funding towards counties who have experienced a disaster that causes damages which exceed the federally set statewide per capita damages threshold. However, FEMA does not strictly adhere to the damages threshold when determining which counties qualify for funding, leading to a fuzzy regression discontinuity design using the level of statewide per capita damages caused by each disaster as the running variable. This identification strategy is valid in determining the causal effect of FEMA funding while the following assumptions are met: first that there is no discontinuity in the baseline distribution of municipality-level spending, or of other covariates, around the cutoff, second that there are no defiers (Hahn, Todd, & Van der Klaauw, 2001). These two assumptions are met in this case because the per capita damages threshold is exogenous to local decision making, meaning that municipalities will decide their expenditure needs based off of the level of damages they experience in a given year which is continuous around the cutoff. Furthermore, in this case a defier would be a municipality that was approved for federal funding but either rejected or chose not to spend it, which I do not observe in this context because my dataset is conditional on having applied for aid.

The statewide per capita damages threshold is public knowledge, so state governors who experience a disaster that caused damages approaching the cutoff have a large incentive to apply, generating sufficient density around the cutoff. However, given the nature of my data, I only observe the statewide damages figures for applicants, and I do not observe the damages figures of other disasters which may have fallen just short of the cutoff but did not apply. Because the threshold is publicly known and my data only includes applicants, I observe a lower density of the running variable to the left of the cutoff (See Figure 2a). Because such a high number of natural disasters occur each year with a continuous level of damages, this result is just a factor of my dataset, meaning that a state governors are more likely to apply for federal funding if they experienced a level of per capita damages that fell above the cutoff such that if I were able to observe the disaster that did not apply for funding, I would see a larger density to the left of the cutoff. This fact could bias my results in that governors who experienced disasters which fell just to the left of the cutoff but did not apply might feel more capable of financing the repairs without federal funding, meaning that their general infrastructure expenditures would be above the average of the states who did apply for aid. This would therefore create a downward bias in my estimates.

PDAs are run jointly between FEMA and the state (the insurer and the insuree), which should imply that they will generate unbiased estimates, but previous studies (Garrett & Sobel, 2003) have indicated that political economy concerns may lead to bunching in the running variable to the right of the cutoff. Figure 2a shows the results of a McCrary test on the running variable, which does indeed show that sorting seems to a play a role in this case. The FRD design does not require continuity in the density of the running variable at the cutoff so long as the conditional expectation of counterfactual expenditure is continuous at the cutoff, which should hold regardless of sorting (McCrary, 2008).

The main identifying assumption behind the fuzzy regression discontinuity is that counties who experience a natural disaster and fall just above the state per capita indicator and receive FEMA funding are, conditional on the vector of controls, comparable to the counties who fall just below the state per capita indicator and do not receive any funding. This assumption implies that there is no discontinuity in the baseline distribution of municipality-level spending, or of other covariates, around the cutoff, implying that any observed discontinuity would be a result of the allocation of federal funds (Imbens & Lemieux, 2008).

As the dependent variables of interest, I use both county and local spending during the fiscal year of the disaster and the fiscal year following the disaster. The reasoning for this is that county and local budgets might be set at the beginning of the fiscal year and thus would not have time to adjust following the event of a natural disaster until the next fiscal year's budget is set. To run the FRD, I can then use eligibility for funding (the instance of assessed per capita damages falling above the threshold) as an instrument for having received funding and estimate the average treatment effect by applying two stage least squares to the following estimating equation:

$$\begin{aligned} Y_{it+k:k\in\{0,1\}} =& \beta_0 + \tau D_{itd} + \beta_1(X_{std} - c_t) + \beta_2 Z_{std} \times (X_{std} - c_t) \\ &+ \beta_3 PA_{it} + \beta_4 HM_{it} + \beta_5 P_{st} + \mu_d + \gamma_s + \lambda_t + \epsilon_{itd} \end{aligned} \tag{1}$$

where D_{itd} is the treatment status equal to 1 if municipality i was included in an approved Public Assistance application for disaster d at time t and is instrumented with $Z_{std} = 1\{X_{std} > c_t\}$ where c_t is the statewide per capita damages threshold in fiscal year t, X_{std} is the level of statewide per capita damages in state s, PA_{it} is the per capita level of public assistance funding that municipality i received from the federal government in fiscal year t from any prior disasters, HM_{it} is the per capita level Hazard Mitigation funding that municipality i received approval for from the federal government in fiscal year t, P_{st} is an indicator equal to 1 if the governor of state s was in the same political party as the president of the U.S. at time t, μ_d are a series of disaster type controls, γ_s is a series of state fixed effects, and λ_t are a series of year fixed effects. Here we can interpret $\hat{\tau}_{FRD}$ as the local average treatment effect of receiving FEMA aid on county level spending at time t: Y_{it}.

This first stage of the FRD is given by:

$$\begin{aligned} D_{itd} =& \beta_0 + \tau Z_{std} + \beta_1(X_{std} - c_t) + \beta_2 Z_{std} \times (X_{std} - c_t) \\ &+ \beta_3 PA_{it} + \beta_4 HM_{it} + \beta_5 P_{st} + \mu_d + \gamma_s + \lambda_t + \epsilon_{itd} \end{aligned} \tag{2}$$

where all variables are defined as in equation (1). The included disasters took place between 2007 and 2019 and I show results for a series of different bandwidths. The largest bandwidth that I use is equal to c_t, which ranges from \$1.24 to \$1.53 over the period, such that observations are included if their level of statewide damages fall within the range $[0, 2c_t]$.

A graphical representation of the first stage is presented in Figure 2b. This estimation uses a triangular kernel function to estimate local linear regressions on either side of the cutoff as well as bins that are evenly spaced and \$0.01 in width. The local linear regressions control for all of the covariates that are included in equation (2). There is a sharp discontinuity at the cutoff which provides a causal estimate of the Local Average treatment for all municipalities that experienced damages approaching the cutoff (Imbens & Angrist, 1994; Imbens & Lemieux, 2008).

It should be noted that this first stage includes observations for the counties and independent municipalities contained within them that applied for FEMA funding via a gubernatorial request. However the level of variation in the running variable is at the state level, meaning that the first stage is effectively a state level regression, weighted by the number of counties and local municipalities affected by each disaster.

I demonstrate that the significance of the first stages is robust to both the inclusion of a series of controls and to a series of different bandwidth options in Table 2 and Table A1, respectively. Column (4) in Table A1 presents the first stage using the Imbens and Kalyanaraman (2012) algorithm which identifies the optimal bandwidth algorithm using a squared loss function. While my first stage results are significant using this bandwidth, it limits the number of distinct disasters that did not receive approval to 6 and thus I have chosen not to use this bandwidth in my preferred specification.

5 Results

The primary objective of FEMA Public Assistance funding is to aid in the removal of debris and necessary repairs following a costly natural disaster. If moral hazard caused by this insurance program is playing a significant role in distorting the way that local municipalities make expenditure decisions, we would expect to see that municipalities that fall just to the right of the cutoff spend, on average, less on construction and maintenance than municipalities that fall to the left of the cutoff. This trend would indicate that counties and local governments are relying on funding from FEMA to finance the upkeep of their local infrastructure rather than budgeting for that upkeep themselves.

I present estimates of the local average treatment effect of FEMA funding on county and municipality-level finances during the fiscal year of, and after, a disaster occurred. Table 3 and Table 4 show the LATE of receiving funding on municipality expenditure decisions in the year of, and the year following, a disaster. We can see that in both years the coefficient on each expenditure category with the exception of total expenditure is negative, meaning that municipalities that receive funding do on average choose to budget less for infrastructure and fire protection services than municipalities that do not receive funding.

The estimates that are significant at the 10% and 5% levels are direct expenditure on general public infrastructure and highways, respectively, in the year following a disaster. I find that counties who applied for Public Assistance funding following a natural disaster spend, on average, \$0.40 less per capita on public infrastructure and \$0.17 less per capita on highway maintenance than counties that did not qualify for federal funding but experienced similar levels of per capita disaster damages the previous year. These results suggest that even controlling for realized aid from previous disasters, counties who receive federal insurance payments may be investing less in the adaptation and maintenance, and therefore in the overall quality of their highways and other infrastructure categories.

In addition to the results shows in Tables 3 and 4, I show a series of local linear regressions estimating the LATE of FEMA funding on per capital local spending and debt in Figure 3 and Figure 4. The regressions in these graphs include the covariates listed in equation (1), and they use a binwidth equal to \$0.15 on either side of the cutoff. We can see that for each expenditure category and total debt outstanding in the year of a disaster, there is a slight decrease in spending to the right of the cutoff, but that the estimates are not tight. Similarly, in the year following a disaster there is a decrease in average spending to the right of the cutoff for every category other than total expenditure. I show in Figure A2 that the average decrease in spending on public infrastructure in the year following a disaster is robust to both a smaller bandwidth and a smaller binwidth.

6 Discussion of the Results

The point estimates of the results shown in Tables 3 and 4 and Figures 3 and 4 conform to my hypothesis that moral hazard is distorting the way that municipalities choose to invest in local infrastructure. We observe that, controlling for the dollar amount of Public Assistance funding that a municipality receives from past disasters in a given year, and for the amount of hazard mitigation funding they are approved for, municipalities that experience per capita damages to the left of the cutoff invest more in infrastructure than municipalities who receive funding. This trend implies that municipalities who do not receive insurance are more likely to invest in decreasing their risk exposure against natural disasters by investing in both the adaptation to, and maintenance of, public infrastructure than municipalities that receive insurance payments. In general, infrastructure that is better maintained or has been adapted to climate risk with suffer fewer damages in future disasters, meaning that counties who invest more in the health and upkeep of their highways and other public infrastructure categories are reducing their own exposure to future risk.

With the exception of total expenditure, the estimates in each budget category are negative in both the year of and the year following a disaster. Further, the estimates for direct expenditure on general infrastructure and highways in particular are significant at the 10% and 5% levels, respectively, in the year following a disaster. It makes intuitive sense that municipalities would be more responsive to insurance payments in the year after a Public Assistance application because most municipalities set a budget at the beginning of the fiscal year and do not deviate from it during the course of the year, even in response to shocks like a natural disaster. This restriction means that municipality budgets are similar to sticky contracts, and thus municipalities can only respond to an exogenous shock, like a severe weather event, in the following year.

These results for every category in the year of a disaster and for the other categories in the year following a disaster, however, are not precisely estimated. If sticky budgets were completely restricting municipalities from changing their expenditure decisions in the year of a disaster we would expect Table 3 to show a series of precisely estimated zeroes, but instead we see imprecise, negative estimates. There are a number of reasons that contribute to the large standard errors that we see in these results. First, the structure of the data source for my independent running variable systematically undersamples counties to the left of the cutoff. Of the 14,027 counties that show up in the Annual Survey of State and Local Finances in either the year of or the year following a disaster, only 1,851 fell below the cutoff while only 2,488 did not receive funding. This small sample to the left of the cutoff leads to higher standard errors for those estimates.[15]

[15] I have tried to combat this issue by supplementing the PDA estimates with both Spatial Hazard Events

Second, there is wide variation of county and local municipality types that are included in the Annual Survey of State and Local Finances. I have cleaned the data to the best of my ability so as to aggregate county-related authorities and assign the correct population to each entity but there is still noise within the data.[16] Furthermore, the Annual Survey of State and Local Finances includes counties with enormous budgets such as Los Angeles and Alameda County, but it also includes a large number of independent municipalities and township which have very little expenditure and little to no expenditure on infrastructure. It was my assumption that these outliers on either side would be randomly distributed on either side of the cutoff, but the outliers have still decreased the overall precision of my estimates.

Nonetheless, I am still able to interpret the point estimates and the change in slopes on either side of the cutoff in my local linear regressions. In the year of a disaster we can see that there is both a negative point estimate at the cutoff and a change in the sign of the slope for direct expenditure on both infrastructure and highways. This may make intuitive sense in that municipalities who fall to the left of the cutoff face increase maintenance and rebuilding costs as they approach the cutoff, thus causing a positive slope, but that municipalities who fall to the right of the cutoff will receive greater government in the form of larger Public Assistance grants as they diverge from the cutoff, leading to a negative slope.

Conversely, we can see that the slope does not change sign for either total debt outstanding or expenditure on fire protection in the year of a disaster or for any of the included financial categories in the year after the disaster. There is also an intuitive explanation for this trend as counties who diverge from the cutoff on the right side of the cutoff both face higher current rebuilding costs and likely to face greater risk from future disasters, thus

and Losses Database for the United States (SHELDUS) and NOAA county, disaster-level damages estimates. Upon merging the SHELDUS and NOAA data to my PDA estimates I found very weak correlations between the damages estimates across sources. As the PDA estimates are federally assessed, uniform in methodology, and are the source of the actual decision making process and discontinuity, I chose to use the PDA estimates without supplementation as my main independent variable. I expand upon the potential reasons for these weak correlations in the Appendix Section A1.2.2.

[16] I describe the cleaning process in further detail in Appendix Section A1.2.1.

meaning that they will spend more this year on disaster protection.

One other plausible explanation for why my estimates may be biased is that natural disasters are not randomly assigned and are often serially correlated in that certain counties often suffer higher damages from disasters on average than others. If certain areas that often often fall above the cutoff receive federal every year or so this regular transfer might cause an improvement in the overall financial health of the municipality, meaning that it has lower debt and higher spending on average. If this theory is true it might be clouding or biasing my estimates.

7 Conclusion

Federal disaster relief programs represent transfer of tens of billions of dollars from the federal government to local governments each year. It is crucial to understand the market distortions that these insurance programs create, and how the promise of federal funds impacts the way that local governments make expenditure decisions. I leverage data on preliminary damages assessments figures for states who applied for federal funding following a natural disaster and data on independent municipality spending, to run a fuzzy regression discontinuity using statewide per capita damages as the running variable.

My first stage is highly significant and shows a clear discontinuity in the probability of receiving funding around the cutoff, indicating that my second stage results can be interpreted as showing a casual estimate of the local average treatment effect (Imbens & Angrist, 1994). In my second stage I find that across three different infrastructure related expenditure categories there is a discontinuity in the way that municipalities that received funding spend as compared to municipalities that did not receive funding. My results show that counties who receive funding spend less, on average, on infrastructure and fire protection than counties who did receive funding, and also hold higher levels of debt in both the year of, and the year following a severe weather event.

The results conform to my hypothesis that FEMA Public Assistance funding disincentivizes municipalities from actively making investments that will decrease their future exposure to climate risk. Counties who receive federal funding rely on Public Assistance funding to finance standard repairs and maintenance to local public infrastructure. These results are important in multiple facets. First, natural disasters will become more and more frequent as the effects of climate change increase, and lower cost natural disasters are already the most common type of costly weather event (IPCC, 2012). Second, the federal government is intending to increase the statewide per capita damages threshold, meaning that in the future a smaller share of disasters will qualify for federal funding (FEMA, 2020). Third, the quality of American public infrastructure is steadily declining and many public goods will deteriorate at a faster rate under the effects of climate change, meaning that large up-front investments in climate adaptation for infrastructure are crucial (ASCE, 2021). These three trends suggest that understanding the decision making process of local infrastructure investments is more important than ever.

Future work should expand upon, and improve the precision of, these findings by filling in the missing disasters to the left of the cutoff, which experienced damages within the bandwidth but did not apply for funding. I believe that per capita damages figures analogous to those assessed by PDAs could be predicted for this subset of disasters, but this exercise is outside of the scope of this paper. Further, it is possible increase the precision of this analysis by leveraging the Freedom of Information Act to request historical PDAs from FEMA dating back to 1988 and by aggregating realized county-level budgets, as opposed to the incomplete survey data used in this analysis, which are publicly available.

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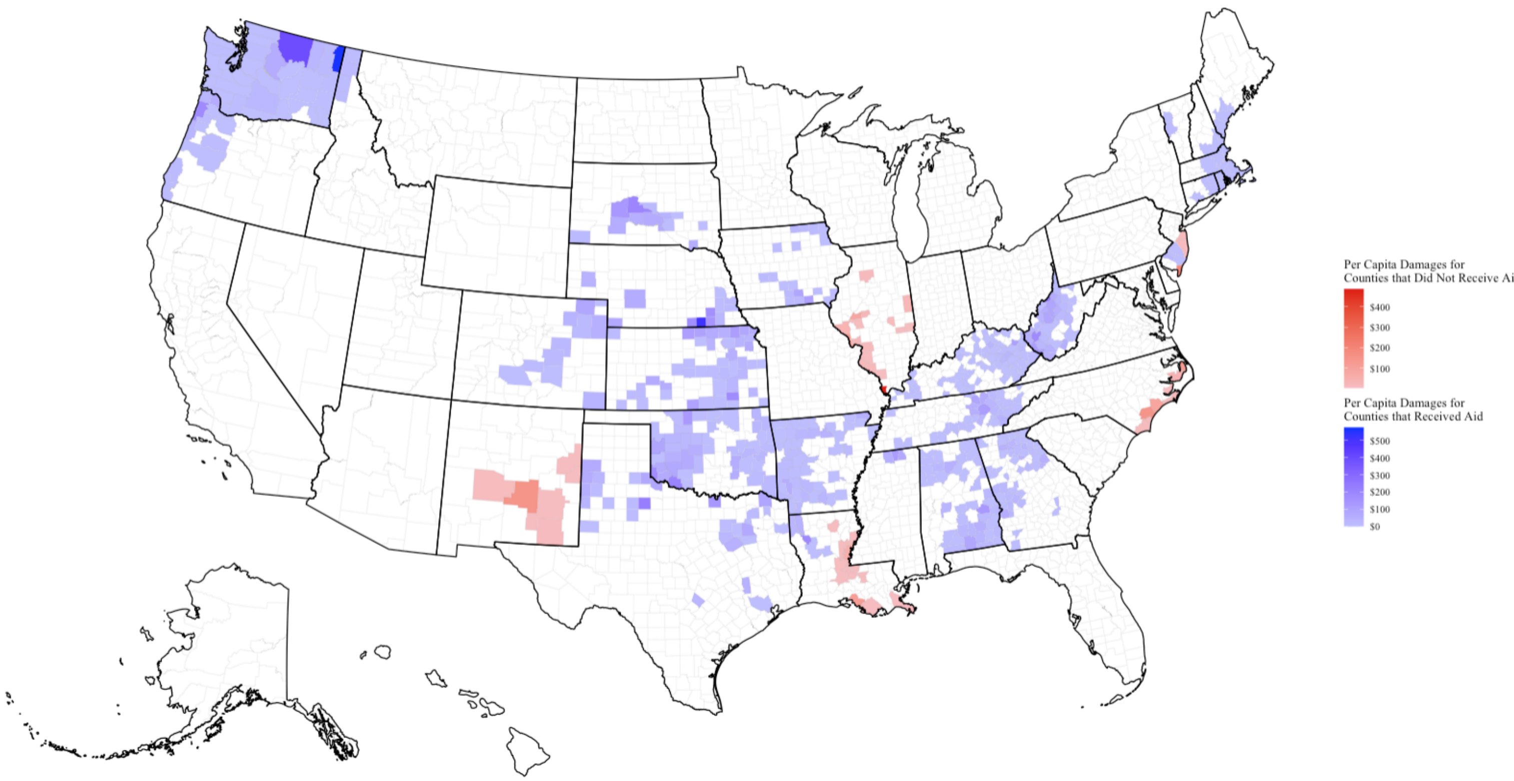
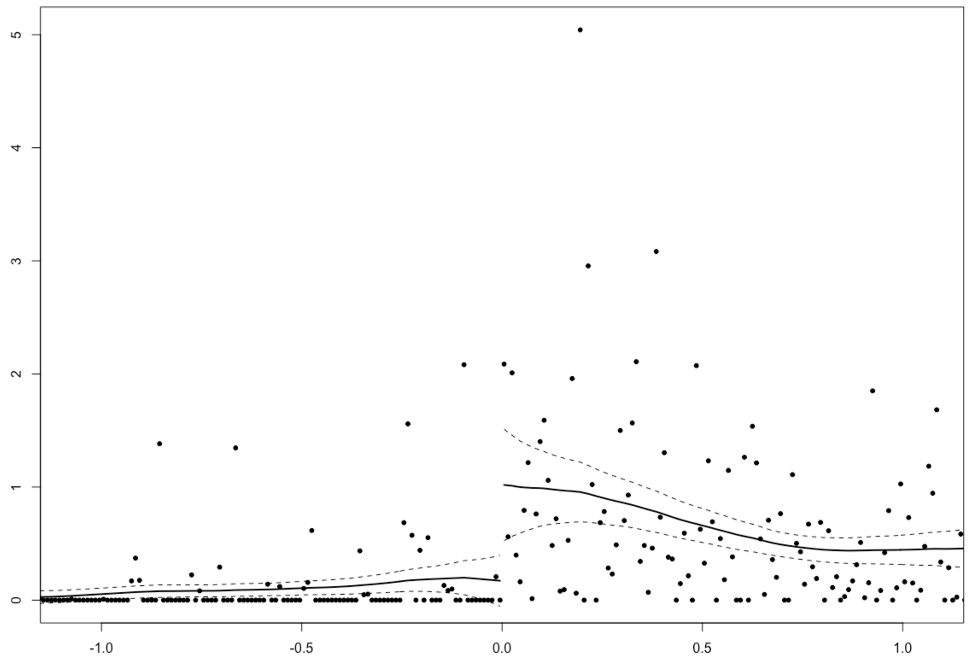
Figure 1: Per capita damages levels in counties that applied for FEMA Public Assistance funding in 2015

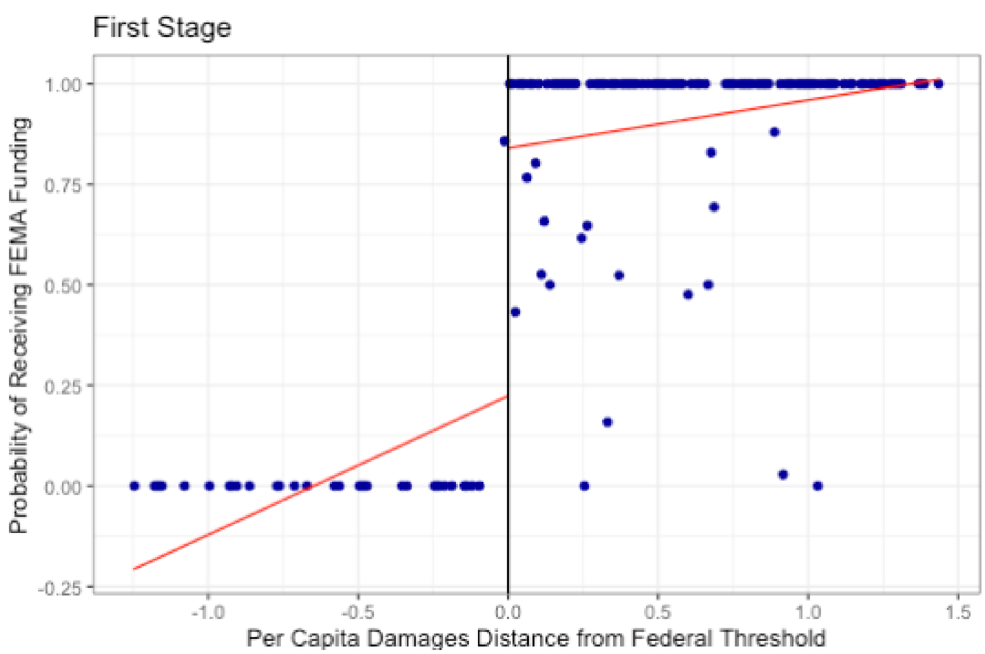


Note: Map shows the PDA assessed damages figures for counties that applied for Public Assistance funding in 2015. Counties in blue were later approved for funding while counties in red were rejected. The deeper the shade of each color, the higher the level of damages. Note that statewide per capita damages figures are used in FEMA's decision to grant funding rather than county-level damages.

Figure 2: McCrary (2008) Sorting Test and First Stage



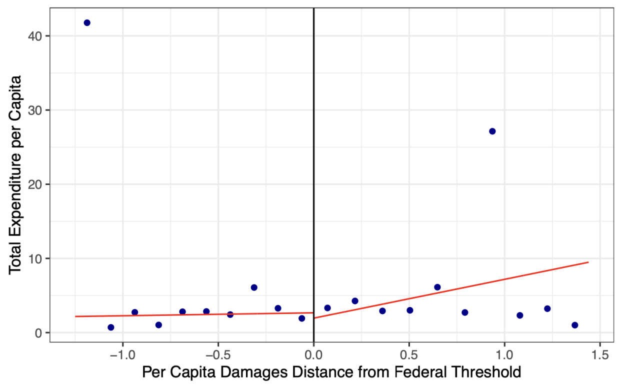
(a) McCrary (2008) Sorting Test of Running Variable



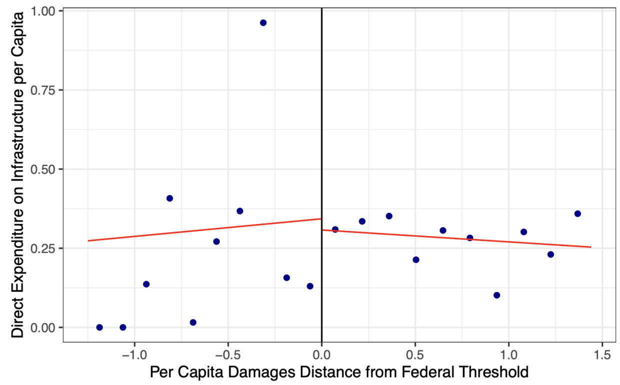
(b) First Stage Results

Note: Figure 2a applies a McCrary (2008) sorting test to analyze the change in density of the running variable at the cutoff. The results demonstrates that sorting may play a role in the assignment of the running variable. Figure 2b shows the jump in probability of receiving treatment at the cutoff. The running variable in this analysis is the distance of the assessed per capita damages from the federally set per capita damages threshold, measured in USD. The local linear regressions in Figure 2b use a triangle kernel function and control for all of the covariates listed in equation (2).

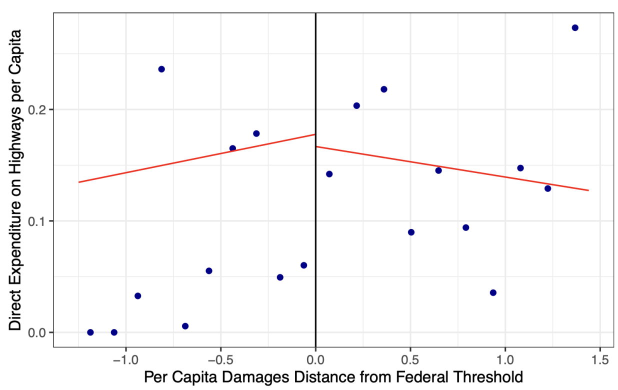
Figure 3: Regression Discontinuity Graphs of Municipality-Level Spending and Debt in the Year of a Disaster



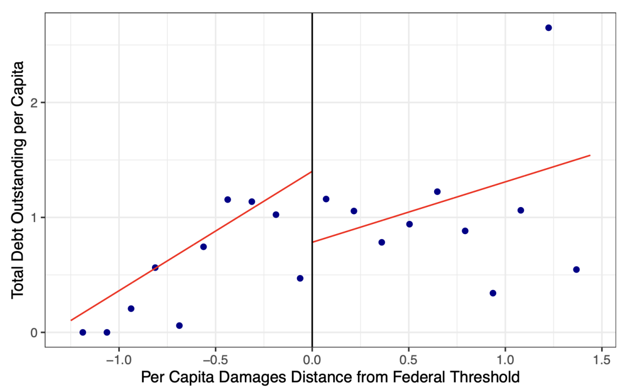
(a) Total Expenditure



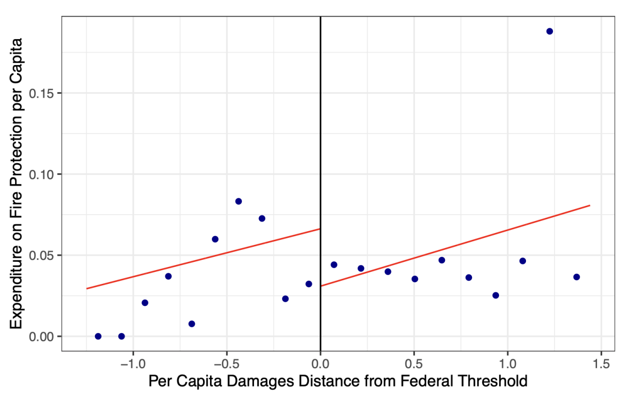
(b) Direct Expenditure on Infrastructure



(c) Direct Expenditure on Highways



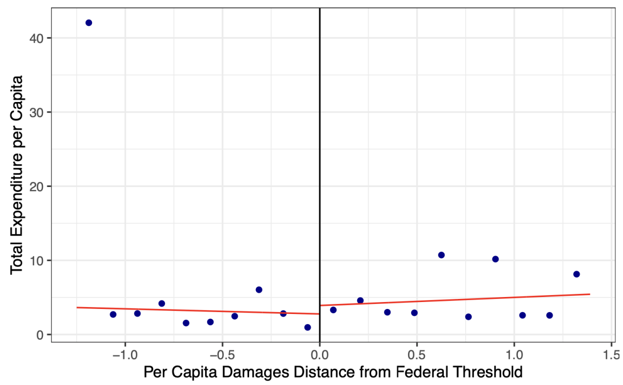
(d) Total Debt Outstanding



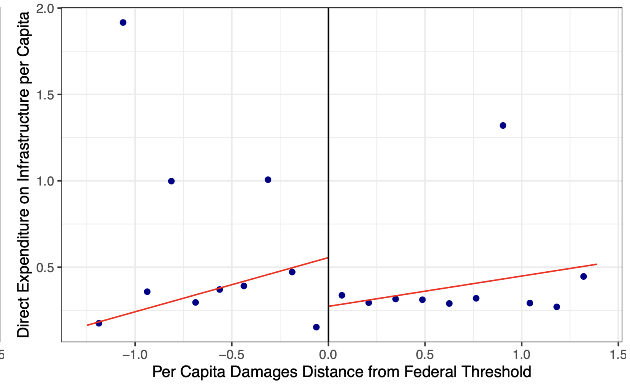
(e) Expenditure on Fire Protection

Note: The bandwidth in the above graphs is equal to statewide per capita damages threshold c_t and the binwidth is \$0.15. Local linear regressions on either side of the cutoff use a triangle kernel. Each regression includes the controls listed in equation 1.

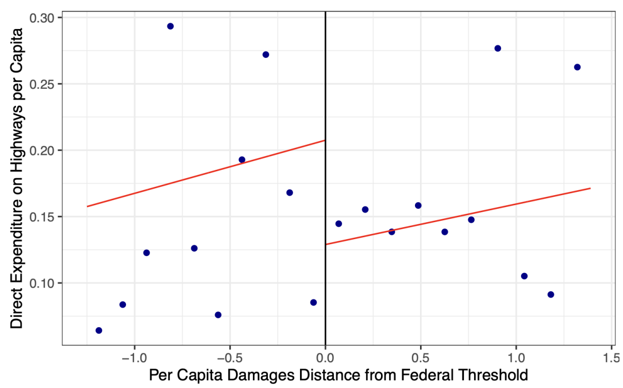
Figure 4: Regression Discontinuity Graphs of Municipality-Level Spending and Debt in the Year Following a Disaster



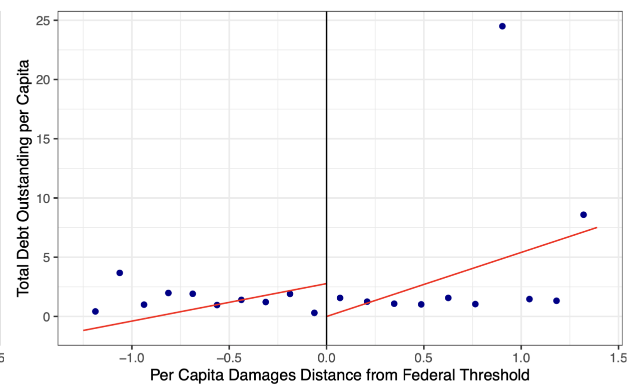
(a) Total Expenditure



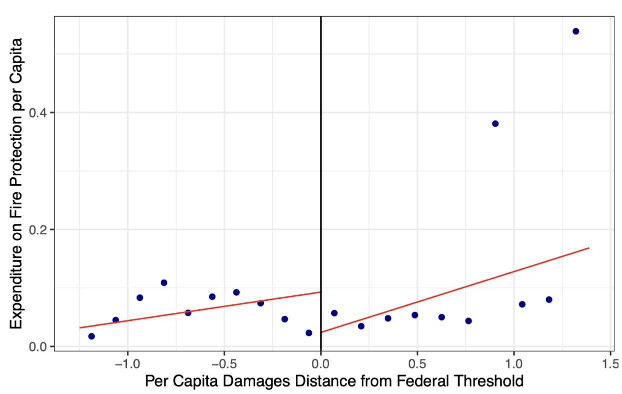
(b) Direct Expenditure on Infrastructure



(c) Direct Expenditure on Highways



(d) Total Debt Outstanding



(e) Expenditure on Fire Protection

Note: The bandwidth in the above graphs is equal to statewide per capita damages threshold c_t and the binwidth is \$0.15. Local linear regressions on either side of the cutoff use a triangle kernel. Each regression includes the controls listed in equation 1.

Table 1: Descriptive Statistics

(a) Statistics on Disaster Damages

	Mean	P10	P50	P90	N
Panel A: Municipalities that did not receive funding					
Statewide per Capita Damages	1.18	0.57	1.11	1.83	2,488
Total Statewide Damages (Millions USD)	9.91	1.21	6.33	20.35	2,488
Same Presidential Party	0.37				2,488
Panel B: Municipalities that did receive funding					
Statewide per Capita Damages	1.98	1.49	1.84	2.56	11,539
Total Statewide Damages (Millions USD)	16.59	2.07	10.12	33.14	11,539
Same Presidential Party	0.41				11,539

(b) Statistics on Municipality Expenditures

	Year of Application				*Year Following Application*			
Expenditure Category	Mean ($)	P10 ($)	P50 ($)	P90 ($)	Mean ($)	P10 ($)	P50 ($)	P90 ($)
Panel A: Municipalities that did not receive funding								
Direct Expenditure on Infrastructure	0.33	0.00	0.12	0.72	0.36	0.00	0.18	0.71
Direct Expenditure on Highways	0.17	0.00	0.04	0.36	0.17	0.00	0.07	0.34
Expenditure on Fire Protection	0.04	0.00	0.00	0.15	0.05	0.00	0.00	0.18
Total Debt Outstanding	0.95	0.00	0.00	2.53	1.21	0.00	0.08	3.07
Total Expenditure	3.47	0.14	1.21	5.03	3.38	0.09	1.11	4.71
Panel B: Municipalities that did receive funding								
Direct Expenditure on Infrastructure	0.36	0.00	0.20	0.73	0.36	0.00	0.20	0.73
Direct Expenditure on Highways	0.15	0.00	0.06	0.38	0.15	0.00	0.08	0.31
Expenditure on Fire Protection	0.06	0.00	0.00	0.15	0.09	0.00	0.00	0.18
Total Debt Outstanding	1.17	0.00	0.01	2.51	2.86	0.00	0.36	3.25
Total Expenditure	4.71	0.20	1.27	4.66	4.64	0.38	1.48	4.98

Note: P10, P50, and P90 indicate the 10th, 50th (median), and 90th percentile of values. Table 1a reports damages figures in USD or millions of USD as specified. The mean of 'Same Presidential Party' refers to the average number of applications that came from governors in the same party as the contemporary US president. Table 1b reports spending per capita for municipalities that applied for a Public Assistance Grant and experienced statewide damages that fell within a bandwidth $[0, 2c]$ of the statewide per capita damages threshold c.

Table 2: First stage with various controls

	Dependent variable:			
	Public Assistance Approved			
	(1)	(2)	(3)	(4)
State Damages Above Threshold	0.618***	0.735***	0.664***	0.787***
	(0.153)	(0.151)	(0.137)	(0.116)
Distance From Threshold	0.322	0.139	0.299*	0.100
	(0.196)	(0.182)	(0.155)	(0.092)
Above × Distance	−0.181	0.030	−0.203	0.010
	(0.191)	(0.143)	(0.143)	(0.061)
Presidential Party	−0.006	0.027	0.008	0.016
	(0.039)	(0.040)	(0.029)	(0.045)
Disaster Controls	×	×	×	
State FEs	×	×		
Disaster Year FEs	×		×	
Observations	14,025	14,025	14,025	14,025
R^2	0.696	0.643	0.624	0.569

*p<0.1; **p<0.05; ***p<0.01

Note: Robust standard errors are clustered at the state level and are in parentheses. The bandwidth here is equal to the statewide per capita indicator, c_t, such that for each year, observations with a statewide per capita impact in the range $[0, 2c_t]$ are included.

Table 3: Second Stage Results Using Equation (1) for Expenditure the Fiscal Year of the Disaster

	Dependent variable:				
	Total Expenditure	Direct Expenditure on Infrastructure	Direct Expenditure on Highways	Total Debt Outstanding	Expenditure on Fire Protection
	(1)	(2)	(3)	(4)	(5)
Received Funding	2.646	−0.072	−0.028	−2.020	−0.134
	(5.506)	(0.129)	(0.053)	(1.856)	(0.108)
Distance From Threshold	−4.462	0.077	0.031	1.197	0.043
	(7.316)	(0.132)	(0.051)	(1.822)	(0.082)
Above × Distance	6.706	−0.093	−0.040	−0.009	0.053
	(6.877)	(0.122)	(0.054)	(2.123)	(0.114)
Observations	11,014	11,014	11,014	11,014	11,014

*p<0.1; **p<0.05; ***p<0.01

Note: Robust standard errors are clustered at the state level and are in parentheses. The bandwidth here is equal to the statewide per capita indicator, c_t, such that for each year, observations with a statewide per capita impact in the range $[0, 2c_{st}]$ are included. County and Local spending figures are measured per capita. Direct expenditure on infrastructure includes spending on highways, parking facilities, sea and port facilities, parks and recreation facilities, housing and community development, sewerage, and solid waste management.

Table 4: Second Stage Results Using Equation (1) for Expenditure the Fiscal Year Following the Disaster

	Dependent variable:				
	Total Expenditure	Direct Expenditure on Infrastructure	Direct Expenditure on Highways	Total Debt Outstanding	Expenditure on Fire Protection
	(1)	(2)	(3)	(4)	(5)
Received Funding	5.862	-0.403^{*}	-0.168^{**}	-4.574	-0.279
	(6.507)	(0.207)	(0.083)	(4.974)	(0.242)
Distance From Threshold	-10.355	0.271	0.136	1.308	0.222
	(10.034)	(0.262)	(0.089)	(4.503)	(0.231)
Above × Distance	10.821	-0.120	-0.082	3.627	-0.016
	(9.270)	(0.329)	(0.083)	(6.386)	(0.189)
Observations	9,814	9,814	9,814	9,814	9,814

*p<0.1; **p<0.05; ***p<0.01

Note: Robust standard errors are clustered at the state level and are in parentheses. The bandwidth here is equal to the statewide per capita indicator, c_t, such that for each year, observations with a statewide per capita impact in the range $[0, 2c_{st}]$. County and Local spending figures are measured per capita. Direct expenditure on infrastructure includes spending on highways, parking facilities, sea and port facilities, parks and recreation facilities, housing and community development, sewerage, and solid waste management.

A1 Appendix

A1.1 Robustness Checks

I chose to use a wide bandwidth equal to the level of the statewide per capita damages threshold in each year in my main specification of equation 2. The reason for selecting this large bandwidth, which ranges from \$1.24 to \$1.53 over the period, was that I observe a small number of rejected funding applications in my data and this bandwidth retains every rejection. To ensure that I am estimating a causal local average treatment effect in my two stage least squares analysis, I ran the first stage of my analysis with a number of different bandwidths to ensure that there is large and positive jump the probability of receiving funding at the cutoff in each case. The results of these checks are shown in Table A1. I do not show graphs for each of these cases because as we can see in Figure 2b, the probability of receiving treatment to the left of the cutoff is consistently 0 at every point other than at \$0.01 below the cutoff.

Further, I show in Figure A2 that my results showing a decrease in average expenditure on infrastructure in the year following a disaster are also robust to a smaller bandwidth of \$0.80 and a binwidth of \$0.04, as opposed to the larger bandwidth ranging around \$1.50 and binwidth of \$0.7 cents shown in Figures 3 and 4. Figure A1 shows that my results showing a decrease in average expenditure on infrastructure in the year of a disaster are not consistently robust to a smaller bandwidth.

A1.2 Data

A1.2.1 Annual Survey of State and Local Government Finances

These data include a full census of the finances of independent municipalities and local governances in years ending in 2 and 7. In the non-census years they rely on survey data with a response rate that typically exceeds 90%.

The Annual Survey of State and Local Government Finances changed their data collection format from wide with overarching budget categories and individual categories to long with individual categories only in 2012. In the overlapping year the data was presented in two different formats, I compared the two different 2012 censuses and found that the long version was more complete. As such I used the wide versions of the data from 2007 to 2011 and the long version for 2012 to 2019. Further, I referenced the data dictionary located in the 2012 Local Government Public Use Files to create overarching budget categories that would be analogous across the two different periods.

To clean these data I first attempted to filter to only public governing entities including counties, towns, and cities and their associated public authorities. To do so I filtered the data to only those observations that contained the strings "COUNTY", "CITY", "TOWN", or "PUBLIC UTILITY" in their ID Name. I then wanted to make sure that I was correctly aggregating county, city, and town related authorities to the correct respective budgets and assigning the correct population to each financial figure. To do so, I aggregated each budget item that was associated with an ID name that contained the string "COUNTY" under the respective counties budget (by taking a sum across all budget items and a maximum of the population options). The remaining issue is that town and city level authorities were not also identified by their respective town or city. As such, I removed a over 100 different authority string options from the ID names that contained either "TOWN" or "CITY" so that I could aggregate total county and town budgets in a similar fashion to the county budgets.

A1.2.2 SHELDUS and NOAA Data

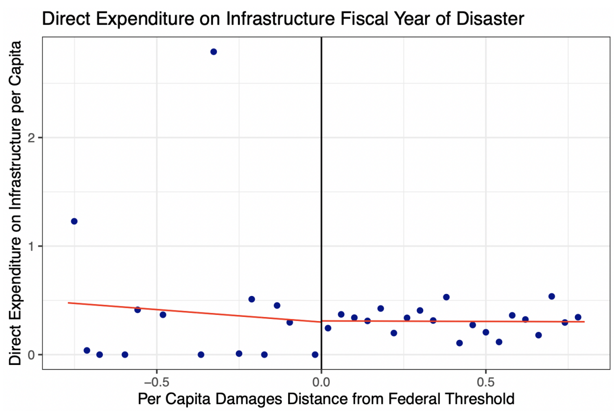
I attempted to leverage data from both SHELDUS and NOAA to combat the systematic undersampling of counties to the left of my cutoff. Both SHELDUS and NOAA data include damages figures on every weather event in the US since the 1960s. In fact SHELDUS uses NOAA data as the basis for its estimates but builds upon them using publicly available information. I had hoped that the damages figures included in these data would be good predictors for the PDA assessed damages that I use to create my running variable, but the correlations between the two estimates were very low.

Some potential reasons for the low correlations are as follows. First, the SHELDUS data is only freely available if aggregated to the county, month level, and does not include a disaster identification number but rather sums damages figures across all disasters within a county month observations. It is very possible that a disaster in my sample would extend beyond a month or occur in a week that breaks across two months, thus making it difficult for me to match to the SHELDUS figures. Furthermore, low cost disasters such as those that are within the bandwidth of the cutoff require precisely estimated damages to have a positive correlation as the per capita figures are so small, so the fact that SHELDUS aggregates damages across disasters adds noise to these correlations.

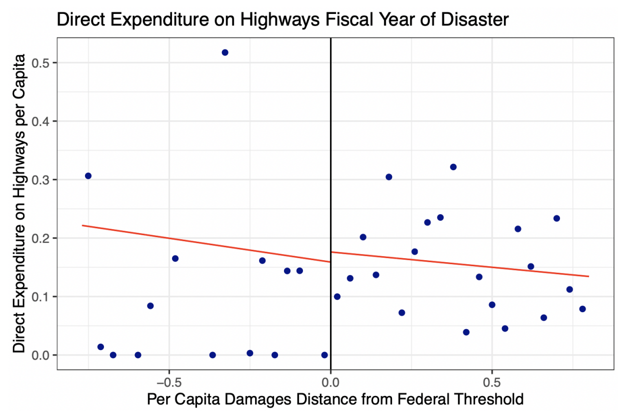
NOAA data, on the other hand, do not aggregate observations to the county, month level and do include a disaster identifier. Nonetheless I faced difficulties matching disasters across the datasets due to the fact that the start date was often off by a day or two or in either the NOAA data or the PDA applications. Further, the NOAA tended to split what would qualify as a single disaster in a PDA application into multiple distinct events that were difficult to identify as being associated with the same overarching disaster.

Lastly, both SHELDUS and NOAA includes estimates of total economic damages while PDAs assess only damages to public goods. These figures might differ wildly in instances where large amounts of private capital or agriculture is damaged but no public goods are even located in the vicinity. A particular example of this is freezing, which can cause severe damage to crops but does not often cause large damages towards public infrastructure.

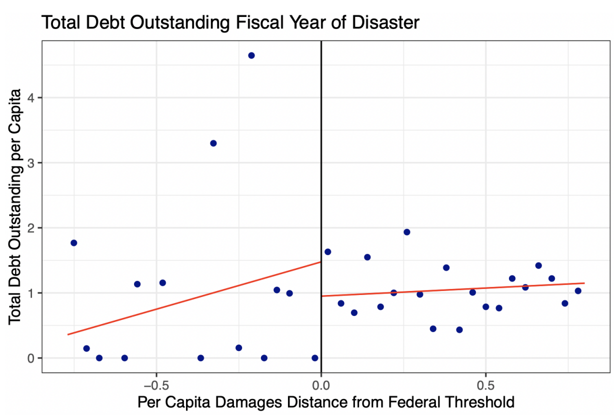
Figure A1: Regression Discontinuity Graphs of Municipality-Level Spending and Debt in the Year of a Disaster



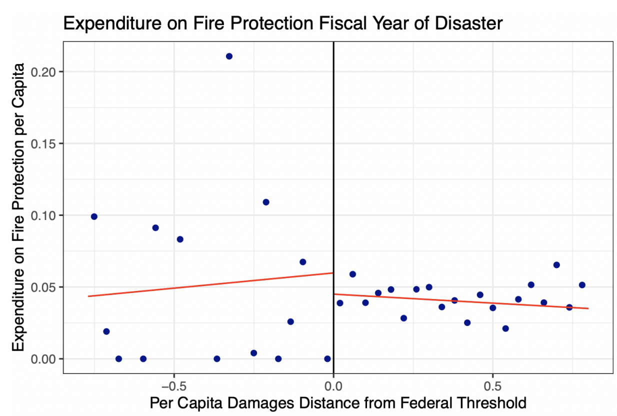
(a) Direct Expenditure on Infrastructure



(b) Direct Expenditure on Highways



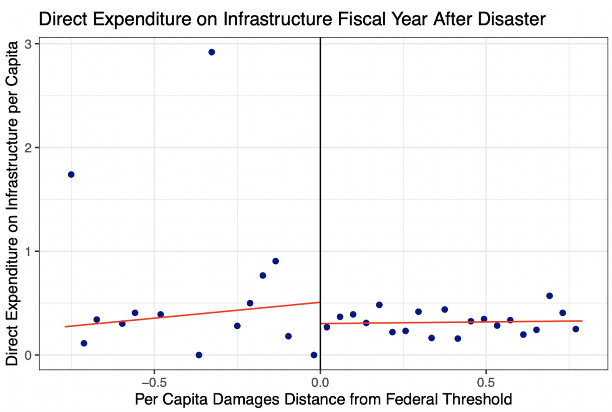
(c) Total Debt Outstanding



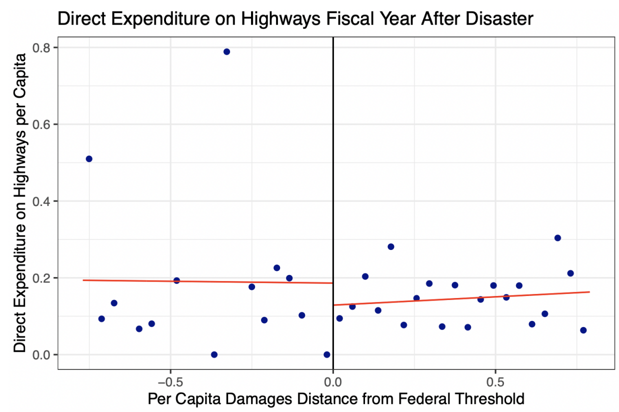
(d) Expenditure on Fire Protection

Note: The bandwidth in the above graphs is equal to \$0.80 and the binwidth is \$0.04. Local linear regressions on either side of the cutoff use a triangle kernel. Each regression includes the controls listed in equation 1.

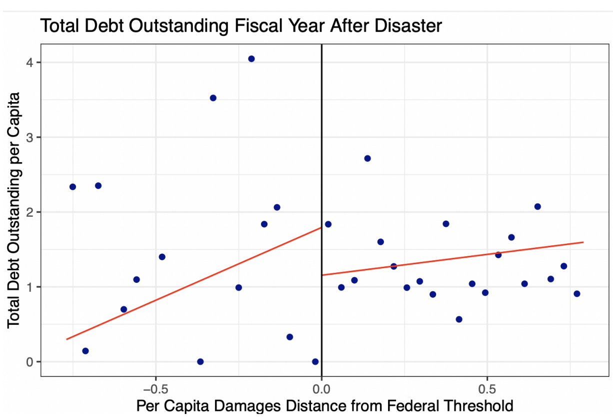
Figure A2: Regression Discontinuity Graphs of Municipality-Level Spending and Debt in the Year Following a Disaster



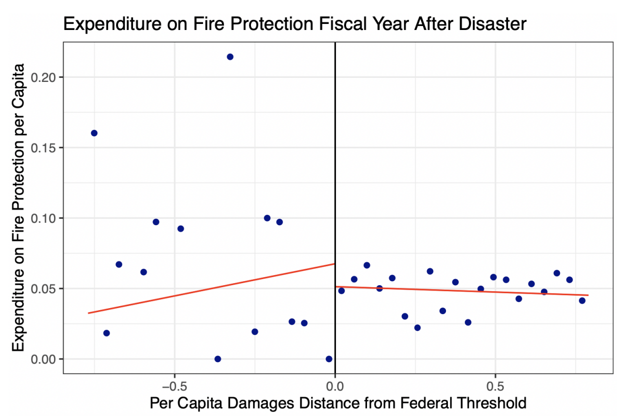
(a) Direct Expenditure on Infrastructure



(b) Direct Expenditure on Highways



(c) Total Debt Outstanding



(d) Expenditure on Fire Protection

Note: The bandwidth in the above graphs is equal to \$0.80 and the binwidth is \$0.04. Local linear regressions on either side of the cutoff use a triangle kernel. Each regression includes the controls listed in equation 1.

Table A1: First stage with various bandwidths

	Dependent variable:			
	Public Assistance Approved			
	(1)	(2)	(3)	(4)
State Damages Above Threshold	0.618***	0.580***	0.525**	0.833**
	(0.153)	(0.183)	(0.227)	(0.340)
Distance From Threshold	0.322	0.605**	1.142*	−18.752
	(0.196)	(0.304)	(0.674)	(13.766)
Above × Distance	−0.181	−0.537*	−1.122	16.549
	(0.191)	(0.310)	(0.742)	(15.372)
Presidential Party	−0.006	−0.045	−0.172***	1.771***
	(0.039)	(0.047)	(0.062)	(0.661)
Observations	14,025	9,629	7,341	1,683
R^2	0.696	0.710	0.783	0.999

*p<0.1; **p<0.05; ***p<0.01

Note: Robust standard errors are clustered at the state level and are in parentheses. The bandwidths in columns (1), (2), (3), and (4), respectively, are equal to the statewide per capita indicator, c_t, \$0.80, \$0.50, and the Imbens and Kalyanaraman (2012) bandwidth, equal to \$0.10. Each regression includes the controls listed in column (1) of Table 2.