Draft: Please Do Not Circulate

Using Rain for Electoral Gain: Evidence from FEMA's Public Assistance Program

Current Version Here

J.J. Naddeo*

September 14, 2020

Abstract

Distributive politics is the study of "who gets what, when, and how". In this paper I find empirical support for predictions produced by a model of political competition at the state-level. To perform my analysis, I construct a novel county level dataset that merges fine-grain physical measures of large destructive storms, satellite data on existing infrastructure, demographic information from Census, and multiple types of relief spending. I find robust evidence that political parties target public spending to counties with higher historic turnout relative to their political neighbors. To give more credence to these results I confirm that each model passes multiple placebo tests. Additionally, to reduce the possibility that my results are driven by some systematic bias, I propose two credible instrumental variables and explicitly model the selection process that determines a counties eligibility for relief aid.

Acknowledgments: I would like to thank Professors Laurent Bouton, Garrance Genicot, and Allison Stashko for their advice and support.

*Georgetown University, Department of Economics

1 Introduction

"Politics is who gets what, when, how."

— Harold Lasswell

In this paper I will focus on, *the who*: citizens living in a county; *the what*: relief aid; *the when*: in response to an exogenous storm; and *the how*: via the state government. While previous literature has studied how state-level politicians may distort public spending[1], I am the first to investigate how the state government as a whole responds to natural disasters. Natural disasters are useful for studying distributive politics since damage is exogenously assigned by nature to each locality. The following analysis processes output from multiple satellites, using geographic information systems (GIS) techniques, to extract fine-grain intensity of roughly 120 storms that triggered aid from the Federal Emergency Management Agency (FEMA). I merge these data with county level demographics, voting behavior, and infrastructure to investigate the role state governments have in redirecting relief aid for political gain. To organize my empirical analysis, I borrow an existing model of political competition. The novelty of which lies in the fact that it explicitly models the border mismatch between political units (state congressional districts) and units in which aid is sent (counties). Specifically, the model provides clear testable predictions that counties with higher turnout relative to their political neighbors will receive larger transfers from incumbent political parties looking to maximize the number of seats they hold in congress. I also compare this framework with existing models of distributive politics that treat the Governor, instead of the state congress, as office of interest. I present this comparison as a step towards future work that examines how political parties balance re-election incentives of both the executive and legislative branches of government.

In the United States, responses to natural disasters are initiated at the federal level. Some programs provide direct aid to citizens that demonstrate need; others grant the state government a large influence on where the marginal dollar is spent. The variation in state

[1] See Strömberg (2004b); Ansolabehere and Snyder (2006)

influence provided by these various programs, presents plausible placebo tests of the model predictions, giving further credence to the results. It has been well documented that FEMA aid lacks stringent requirements and oversight,[2] offering an environment where one should expect political distortions. Indeed, I find evidence that supports the model predictions: that the flow of FEMA's Public Assistance dollars is influenced by a counties historic turnout levels relative to its political neighbors. These distortions are not driven by a single state, nor a single storm, and are robust to numerous econometric strategies. These results provide evidence that in citizens' time of need, political parties direct aid to localities that will help win future elections. As storms increase in intensity due to climate change and gerrymandering creates larger electoral incentives for targeting it is probable that this distortion will only grow in magnitude.

The paper proceeds as follows, section 2 elaborates on some points made in this section and provides context by reviewing pertinent literature, section 3 will lay out model of an incumbent party maximizing representation in a state congress, and discuss the empirical predictions it generates. Section 4 will describe the most unique feature of this paper, the data. Section 5 will discuss the empirical strategy employed to identify unbiased estimates of the model parameters. Section 6 will present empirical results predicted by the model. Section 7 will summarize and contextualize the results and conclude.

2 Literature

Much of the literature on distributive politics attempts to establish a casual link between how politicians allocate non-programmatic public spending and characteristics of localities. In these investigations, attributing a shift in spending to a specific politician or party is paramount. Most papers do this by focusing on spending programs that have relatively high temporal variation, and then attributing a change to the politician in office during the

[2] See articles in Wired and The New York Times. Leeson and Sobel (2009) also documents a link between corruption and FEMA aid.

change. For example, in Berry et al. (2010); Aidt and Shvets (2012) the authors focus on spending programs that have high coefficients of variation.[3] The authors concentrate on this highly variable spending to avoid large programmatic expenditures, built over generations of politicians, that transfer money to geographic diffuse populations because "*It hardly seems appropriate to attribute this kind of spending to the immediate efforts of the president or other policy makers.*"[4] Instead of focusing on the historic variability of a spending program, I use the fact that politicians are tasked with responding *immediately* to exogenous disasters. This setting allows me to better study the true preferences of political parties in power, because they have full control over the spending program and are unfettered by any status quo inertia of previous politicians.

The current literature struggles to control for the distribution of need for public spending. An ideal research design would control for the locality characteristics that determines need; thus, any political distortions can be seen as a departure from the welfare maximizing allocation.[5] Studying distributive politics using natural disasters provides numerous proxies for need. I will group these variables into three major groups: infrastructure, damage, and vulnerability and leave specific discussions of each for later.

In the United States, citizens are in contact with their state and local governments much more than the federal government. Control of state legislature allows a political party a unique ability to influence future electoral success. For example, state legislatures are tasked with drawing district maps, which in turn have a major impact on the electoral success of a party, not only at the state but also federal level. The state legislature plays a large role in determining the state budget.[6] Thompson (1986) and Thompson and Moncrief (1988) provide extensive reviews of the state budgeting process and conclude that parties

[3]This strategy was originally adopted by Levitt and Snyder (1997, 1995)

[4]Berry et al. (2010)

[5]See Moser (2008) for a study that attempts to show how political incentives distort the "poverty minimization" objective of spending programs in Madagascar.

[6]See Goodman (2007) for a review. Even if the Governor holds more power over relief spending, I will assume that their behavior internalizes the competition for control over the state lower house, and therefore will spend money to influence state house elections.

play large roles in determining who gets what. For this reason, I explicitly model party competition for seats in the lower statehouse. There is also a dedicated discussion toward the conclusion of this paper that contrasts this model with a model with the Governor as the sole actor as in Strömberg (2004b).

There is a robust literature on the political nature of relief aid. The current paper is unique in that it exams distortions of relief spending caused by political competition at the state level. Rather, the literature focuses on interactions between the executive branches of the federal and state government, namely the governor and President. In the United States, a disaster declaration request is submitted by the governor and either accepted or rejected by the President. Garrett and Sobel (2003) and Sobel et al. (2007) study declaration rates and expenditure at the state level and find that almost half of all FEMA aid is used as a political instrument by the President and members of congress on the FEMA sub committees. They document that even after FEMA was merged into the Department of Homeland Security, political distortions persisted. Downton and Pielke (2001) focuses on responses to severe floods and similarly finds that Presidential re-election motives drive response, not need. Additionally, Sylves and Buzas (2007) finds that Presidents are more likely to declare disasters during re-election years. Salkowe and Chakraborty (2009) also notes that there is a positive correlation between declarations and Presidential election years but no evidence that partisanship plays a role in decision making. Moving towards the state level, Gasper and Reeves (2012) demonstrates that governors make disaster requests strategically, especially when they are not facing a term limit. Reeves (2011) focuses on the President's strategic behavior and shows that competitive battleground states can expect to receive twice as many Presidential disaster declarations compared to less competitive states. He also shows that this strategic targeting pays off, voters reward presidents for declarations. This leads us into the next empirical fact documented by studies on the political economy of relief aid, the electorate responds to spending after natural disasters. Gasper and Reeves (2011) find that voters are sophisticated enough to reward governors who request aid, and punish presidents who withhold it. Healy and Malhotra (2009) also investigates both the governor's strategic behavior and voters response. They show that voters provide incentives for politicians to shirk preparedness spending in favor of sub-optimal (in a societal welfare sense) relief aid following natural disasters. There is also a literature showing positive voter response in Germany (Bechtel and Hainmueller, 2011), India (Cole et al., 2012), and Canada (Bodet et al., 2016). These results provide evidence that voters are responsive to relief aid, a key assumption that will be used in this paper.

The distributive politics literature has identified other characteristics that may influence political targeting, most prominently information and "swingness",[7]. I will attempt create proxies for both information and swingness, while focusing on turnout as the determinant of interest.[8] A key statistic that signals the health of a democratic society is the turnout rate of its citizens. There is a robust literature that attempts to model the determinants of turnout.[9] While there have been numerous plausible explanations for empirical observation of substantial turnout, the current literature has not come to a consensus on the paradox of (not) voting. The current study will take the stylized fact that people turn up to the polls at face value, assuming turnout is an exogenous feature of a county that politicians take as given when optimizing.

I borrow a probabilistic voting model of political competition developed by Genicot et al. (2018) to organize empirical findings. [10] The model consists of two parties located on a political spectrum, which compete for votes from citizens that have fixed ideological preferences. A consistent assumption is that, parties promise transfers that induce utility differentials that can outweigh these preferences. Depending on the assumptions made about the responsiveness of voters to transfers from each party, these models can predict that the

[7]Swingness is a term used to denote voters with weak party attachment, that is to say that they can be *swung* to vote for either party.

[8]One reason for this is that turnout can be directly measured, whereas information and swingness are often hard objects to measure.

[9]See review in Myatt (2015) for a good recent overview of turnout literature.

[10]This model traces its origins back to the seminal works by Cox and Mccubbins (1986); Lindbeck and Weibull (1987); Dixit and Londregan (1996).

optimal[11] allocations target one of two groups: 1) *swing* voters without strong ideological leanings or 2) *core* voters that support one party strongly. As shown in Golden and Min (2013) empirical tests of these voter-level theories are fraught with inconsistencies and usually test a weaker prediction about swing vs. core localities. For example, there is ample empirical evidence that Presidential disaster declarations are targeted to states that are electorally important (known as *swing* states). However, this does not necessarily support the swing theory because little is known about what localities *within* the state are targeted. Furthermore, it is unknown which citizens *within* these localities receive the aid. My results provide evidence that parties target counties whose citizens have historically shown up at the polls. That is, parties target localities that are responsive in the sense that they have a large *relative* share of active voters. The term relative is emphasized here, because it highlights the innovation of the model used in this paper: targetable counties can contain multiple districts and share them with numerous other counties. In previous papers targetable groups are assumed to be nested within a district.[12] Specifically, I utilize the administrative fact that states are constrained to send transfers to counties. These counties have boundaries stable boundaries over time, most being drawn decades ago. Conversely, state congressional districts have lines that change every ten years according to changing demographics and regularly cut across multiple counties. This means that county and district borders frequently overlap. Prior literature acknowledges the existence of such counties but either removes them from the sample (Berry et al., 2010), splits them by surface area (Aidt and Shvets, 2012), or by simply averages across all districts (Ansolabehere et al., 2002).

3 Model

In this section, I will present a theoretical model developed by Genicot et al. (2018). It was further adapted by Stashko (2020) to be applied at the state level in the United States. It

[11] In the electoral sense.

[12] See Lindbeck and Weibull (1987); Cox and Mccubbins (1986); Dixit and Londregan (1996); Battaglini (2014); Strömberg (2008)

models the decision process of a ruling political party, that is attempting to maximize the number of seats controlled in a state congress, while being constrained to transfer funds at the county-level. Strömberg (2004b) develops a similar model and assumes instead that the Governor controls the state spending. A brief discussion on a possible extension that merges both of these models can be found in section 6.2.

Let a continuum of citizens be divided among a finite number of, C, counties and D districts. District lines are redrawn by the state government after each decennial census while county lines remain fairly constant over time. This process creates maps where district lines cross over multiple counties. Let the number of citizens living in county, c, and district, d, be represented by $n(c,d)$. As required by law, all districts contain the same population, normalized to 1 (i.e. $\sum_c n(c,d) = 1$) and county populations, n_c can vary (i.e. $\sum_d n(c,d) = n_c$). Only a portion of the citizenry votes. A share, $e(c,d) \in [0,1]$, of citizens are eligible to vote (e.g. meet age requirements and are not felons). Of these eligible voters a fraction, $t(c,d) \in [0,1]$ decide to turnout to vote.[13] Therefore, one can write the total *number* of citizens that live in county, c, and vote in election for district, d as $T(c,d) = n(c,d)t(c,d)e(c,d)$.

3.1 Party Maximization Problem

The timing of the model is as follows, a disaster occurs and the ruling party is given a budget exogenously to allocate to counties.[14] The party has correct beliefs about the distribution of ideological preferences defined below. Voter's observe this spending and then vote in the next election accordingly. As with most probabilistic voting models the parties objective function can be written as:

$$\max_{q_c} \sum_d p_d \tag{1}$$

$$\text{s.t.} \quad \sum_c q_c \leq y$$

[13]In this model it is assumed that the turnout rate of a county-district unit is exogenous and known to both parties by observing previous election results.

[14]The party can be thought of as a strategic governor that places an emphasis on controlling congress.

Where y is the total budget for transfers, which in this paper is exogenously determined by the federal government's assessment of need after a storm. Let p_d be the probability that the ruling party wins district d. In this model a voter makes her decision by comparing the utility from disaster response, to her per-existing ideological preferences. Specifically, a voter will vote for the incumbent party iff

$$u_c(\mathbf{q}) > \eta + \nu_i \tag{2}$$

Let ν_i be the idiosyncratic preference shock for the incumbent party. Let η be an aggregate shock which can be interpreted as any state-wide election news that strikes shortly before a voter casts their vote. As is standard in all probabilistic models the political party in power correctly forms expectations over η and ν, which follow the following uniform distributions:

$$\nu_i \sim \text{Unif}\left(\sigma_{cd} - \frac{1}{2\phi}, \sigma_{cd} + \frac{1}{2\phi}\right) \tag{3}$$

$$\eta \sim \text{Unif}\left(-\frac{1}{2\gamma}, \frac{1}{2\gamma}\right) \tag{4}$$

As has been pointed out previously (Lindbeck and Weibull, 1987; Persson and Tabellini, 1999) $\phi > 0$ is directly proportional to the fraction of voters that are ideologically indifferent between the incumbent and challenging party. These "indifferent" voters are referred to as *swing* voters because they can be swung via a small change to $u_c(\mathbf{q})$. For the following analysis I hold this swing parameter constant.[15] In this model it is also assumed that there exists "swingable" voters in all county-district intersections.[16] The probability that the incumbent party wins district d in the next election can be written in closed form as:

[15] I do this empirically by proxying for swingness using the coefficient of variation of county-level turnout and how close historic elections have been to 50-50.

[16] **Swingability:**

$$u_c(\mathbf{q}) - \sigma_{cd} - \eta \in \left(-\frac{1}{2\phi}, \frac{1}{2\phi}\right) \ \forall q, \eta, \text{ and } d \text{ s.t. } n(c,d) > 0 \tag{5}$$

$$p_d = \Pr\Bigg(\big[\sum_{c \in d} T(c,d) \; \Pr\big(i \in c \text{ votes for incumbent}\big) \big] \geq \frac{1}{2} \Bigg) \tag{6}$$

Utilizing the condition for citizen i casting her vote for the incumbent party, given in equation 2, and that the party forms correct expectations over the distribution from which idiosyncratic shocks are drawn we can define the following:

$$\Pr\big(i \in c \text{ votes for incumbent}\big) = \frac{1}{2} + \phi\Big(u_c(\mathbf{q}) - \eta - \sigma_{cd}\Big) \tag{7}$$

Taking the probability over the aggregate shock η leaves us with the final expression for p_d:

$$p_d = \gamma \frac{T(c,d)}{\sum_{c \in d} T(c,d)} \big(u_c(\mathbf{q}) - \sigma_{cd}\big) + \frac{1}{2} \tag{8}$$

Thus the probability of the incumbent party winning district d is just the weighted average of the parties vote shares in each county, weighted by the share of district turnout living in each county. This expression can now be inserted into equation 1. The last object that needs to be defined is the function that represents the utility gained from a transfer. For this I follow Stashko (2020), who follows Strömberg (2004b), in picking a utility function that produces predictions that can be directly tested.

$$u_c(q) = \frac{a_c}{1 - \frac{1}{\rho}} \left(\frac{q}{n_c^{\alpha}} \right)^{1 - \frac{1}{\rho}} \tag{9}$$

Let $\rho \in (0,1)$ and $\alpha \in [0,1]$. Where a_c is a county specific term that determines the utility gained from a transfer and n_c is the population of county c. Notice that α determines how much the population affects the county-wide utility, said another way, α allows us to determine if the transfer is valued as a public or private good. For example, an $\alpha = 0$ implies the transfer is public, in that the utility is not modulated by population of the county.

To ensure an interior solution, one must assume that all districts are *contestable*, in that

p_d does not equal 0 or 1 for any of the districts.[17]

The probability of winning district, d changes with a change in transfer to county $\tilde{c}$.[18]

$$\frac{\partial p_d}{\partial q_{\tilde{c}}} = \gamma \frac{T(c,d)}{\sum_{c \in d} T(c,d)} \frac{\partial u_{\tilde{c}}}{\partial q_{\tilde{c}}} \tag{11}$$

From this, one can start to gain intuition about how political parties will "target" spending to counties that have a higher share of a districts turnout. For example, imagine four counties that share two districts, as shown in figure 1 below. In this example, counties a and b are identical across all observables. However, county a is "stuck" with a high turnout neighbor.[19] Looking at equation 11 one can understand this targeting as simply equating the

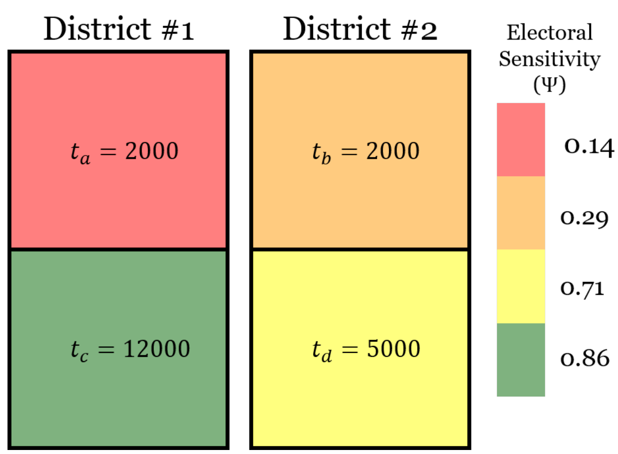

Figure 1: Let all four counties have the identical populations and socioeconomic distributions. The only dimension that is allowed to vary is turnout, t. Notice that counties a and b have the same turnout, however county b will receive more funding because it has a higher share of district 2's votes.

marginal changes in winning probabilities. The higher share of a districts turnout $\frac{T(c,d)}{\sum_{c \in d} T(c,d)}$ the higher marginal return a party receives from increasing relief spending.

[17] **Contestability:**

$$\frac{T(c,d)}{\sum_{c \in d} T(c,d)} (\Delta u_c(\mathbf{q}) - \sigma_{cd}) \in \left(-\frac{1}{2\gamma}, \frac{1}{2\gamma} \right) \tag{10}$$

I empirically satisfy this condition by omitting any county that was solely inside an uncontested district where party data is available (this is only an issue in two storms that use pre-2000 election data from OK and TX)

[18] Note that this expression does not account for the fact that a county may share *multiple* districts, this point will become salient when I formally write out the first order conditions later.

[19] In this context neighboring counties are defined as counties that share a district.

3.2 Testable Implications

As mentioned earlier, the utility specification allows for the first order condition of equation 1 to be taken directly to data. Formally, there exists a positive Lagrange multiplier, λ common to all counties. Such that for all counties the following condition holds

$$\frac{\partial \sum_d p_d}{\partial q_c} = \sum_d \gamma \frac{T(c,d)}{\sum_{c\in d} T(c,d)} \frac{\partial u_c}{\partial q_c} - \lambda = 0 \tag{12}$$

Plugging in the utility function and taking the natural logarithm of equation 12 results in the following equation.

$$ln(q_c) = \rho ln\left(\sum_d \frac{T(c,d)}{\sum_{c\in d} T(c,d)} \right) + (1-\rho)\alpha ln(n_c) + \rho ln(a_c) - \rho ln(\frac{\lambda}{\gamma}) \tag{13}$$

Assuming as in Strömberg (2004b) that variation in a_c can be captured via a linear combination of county-level observables one can directly estimate equation 13 to test for the presence party competition. Furthermore, the number of representatives[20] in a county is something that can be precisely measured by observing district maps. For this reason, Stashko (2020) makes the following substitution in equation 13:

$$\sum_d \frac{T(c,d)}{\sum_{c\in d} T(c,d)} = R_c \left[\sum_d \frac{1}{R_c} \frac{T(c,d)}{\sum_{c\in d} T(c,d)} \right] \tag{14}$$

Notice that substituting this into equation 13 provides another testable specification:

$$ln(q_c) = \rho ln(R_c) + \rho ln\left(\frac{1}{R_c} \sum_d \frac{T(c,d)}{\sum_{c\in d} T(c,d)} \right) + (1-\rho)\alpha ln(n_c) + \rho ln(a_c) - \rho ln(\frac{\lambda}{\gamma}) \tag{15}$$

This specification identifies the parameter ρ using variation in the number of representatives R_c, an observable that again has zero measurement error. This specification also predicts that the coefficients in front of the first two terms be equal, a more demanding test

[20] Which is equivalent to the number of districts running, in single member districts

of the model.

4 Data

One of this paper's novelties is the uniqueness of the constructed data-set To the extent of my knowledge, this is the first paper that merges state election data measured at the precinct level, pixel level rainfall, wind-speed simulations, media maps, and census data together. Merging data at such a fine geographic level allows me the ability to answer interesting questions that were previously understudied.

4.1 State-Level Elections

To measure historical turnout for each county-district pair I build on the amazing work by Ansolabehere et al. (2014) (HEDA henceforth) and the team from OpenElections.[21] HEDA and OpenElections provides state-level election turnout (by party) for all 17 states in my sample at the *precinct* level. I supplement this data by scraping individual secretary of state websites when available, to ensure that there are no missing counties and/or districts. Precincts are small geographic areas that are rarely split by any other administrative boundary. This feature enables researchers to study smaller geographic areas, such as intersections of counties and state legislative districts. For most states I am able to collect election returns from the late 1990's until the most recent elections. The model assumes that the turnout within a county-district is exogenous characteristic of the locality, immutable by the political party. A similar problem is faced by the literature that studies the advantage enjoyed by incumbent candidates, this literature attempts to identify a parties "normal vote" by averaging over numerous previous elections.[22] I follow this same strategy and average election returns over the previous three elections prior to a storm.

[21] Accessed here: `https://github.com/openelections`

[22] See Ansolabehere et al. (2000).

4.2 FEMA Data

In this subsection I describe how I pulled county level funding data from FEMA using OpenFEMA. OpenFEMA's stated goal is "*to execute federal open data machine readable policies and standards, and to promote a culture and empower open government within FEMA.*" I focus on two programs run by FEMA in response to natural disasters: 1) Individual Assistance Program (IA); 2) Public Assistance Program (PA). Each program provides funding data at the county-level for each major disaster declaration. After dropping disasters where damage cannot be plausibly captured by rain and/or wind-speed (e.g. snow storms, fires, tornadoes, etc.), and those that do not have state-level election data, I am left with 129 disasters affecting 11,316 counties from 2003-2017. A description of the structure of each program is essential to interpreting the following results. The IA program is meant to provide individual homeowners and renters "financial help or direct services to those who have necessary expenses and serious needs if they are unable to meet these needs through other means. Up to $33,000 (adjusted each year) is available in financial help".[23] The PA program is a larger FEMA program that "provides emergency assistance to save lives and protect property, and assists with permanently restoring community infrastructure affected by a federally declared incident."[24] Each project in the PA program is split into 8 categories: Category A: Debris removal; Category B: Emergency protective measures; Category C: Roads and bridges; Category D: Water control facilities; Category E: Public buildings and contents; Category F: Public utilities; Category G: Parks, recreational, and other facilities; and Category Z: Administrative Costs. FEMA further aggregates projects into two major categories: 1) Emergency work (Categories A and B) and 2) Permanent work (Categories C-G). The split in spending is roughly equal[25] between these two categories with the major difference being the timing of spending. As the names suggest, the Emergency Work spending is spent within

[23]Taken from official FEMA document here

[24]Taken from FEMA fact sheet accessed here.

[25]In my sample, the average amount of emergency spending is 112 million 2012 USD per disaster and the average amount of permanent spending is 143 million 2012 USD per disaster.

days-weeks of the disaster, whereas the Permanent Work spending occurs months-years post disaster. To my knowledge, this is the first paper that exploits the administrative feature that PA spending runs through the State government and therefore is susceptible to political distortions.

4.3 Measures of Damage and Infrastructure

The model predictions require locality-level, in this case county-level, controls that affect how much the locality values the relief spending as in Strömberg (2004b). After a natural disaster a counties utility is assumed to be an increasing function of damage. A major critique of most studies investigating the economic impacts of natural disasters, is the use of endogenous and/or imprecise measurements of damage. Felbermayr and Gröschl (2014) propose using physical measurements of storms as an exogenous way to measure storm intensity. An added benefit to measuring storms using physical quantities (e.g. rainfall and wind speed) is that these measurements have very fine spatial resolution and can pick up heterogeneous damage between small localities. In this paper I will focus on major disaster declarations initiated by large storms and hurricanes. For all major storms, massive rainfall will contribute to a large amount of damage (e.g. mass flooding). To control for rainfall, I utilize continuous measures from two sources using the Giovanni online data system:[26] 1) For all storms occurring before March 12^{th} 2014 I extract rainfall utilizing Phase 2 of the North American Land Data Assimilation System (NLDAS-2)[27] which reports precipitation (in mm) at a spatial resolution of 0.125° x 0.125° [28]; 2) For all storms occurring after March 12^{th} 2014 I extract rainfall utilizing the Integrated Multi-Satellite Retrievals (IMERG) for the Global Precipitation Measurement (GPM) mission which reports precipitation (in mm) at a spatial

[26] Analyses and visualizations of rainfall data used in this paper were produced with the Giovanni online data system, developed and maintained by the NASA GES DISC.

[27] See Xia et al. (2012) for information on model.

[28] For context this is roughly 14 km by 14 km at the equator.

resolution of 0.1° x 0.1°.[29] I collect precipitation data for the entirety of the storms[30] in my sample and then use GIS software to average across all pixels that fall within the boundaries of a county.[31] The literature has noted that storms producing sustained wind speeds greater than 20 $\frac{m}{s}$ inflict a large amount of wind damage. In my sample there are currently 52 such high wind-speed storms. To control for wind damage during these storms I downloaded storm characteristics from the National Oceanic and Atmospheric Administration's (NOAA) International Best Track Archive for Climate Stewardship (IBTrACS).[32] Anderson et al. (2018) developed a package in R that takes as an input storm tracking data and then outputs wind speeds at specified grid points using a wind speed model developed in Willoughby et al. (2006). The model solves for the wind speed at each grid point in 15 minute time steps then outputs: 1) Maximum value of surface-level (10 meters) sustained winds, in meters per second; 2) Maximum value of surface-level (10 meters) gust winds, in meters per second; 3) Length of time, in minutes, that surface-level sustained winds were above a certain wind speed cutoff (e.g., 20 meters per second); 4) Length of time, in minutes, that surface-level gust winds were above a certain wind speed cutoff (e.g., 20 meters per second). Conveniently the package in Anderson et al. (2018) is optimized for storms in the Atlantic Basin and outputs wind speed measurements at population centroids[33] of all affected US counties. An example of visual output from the model is provided in Figure 2.

While rainfall and wind-speed are both plausibly exogenous measures of damage, one may worry that two counties receiving the same rainfall and/or wind speed may experience vastly different levels of "damage" due to variation in the presence of infrastructure. In an attempt to control for the amount of infrastructure present in a county I utilize the Global Man-made Impervious Surface (GMIS) Data-set derived from Landsat imagery.[34] The GMIS

[29] For context this is roughly 10 km by 10 km at the equator.

[30] In order to capture the full extent of the storm I start collection 1 day before the "start" of the storm and 1 day after the "end" of the storm.

[31] County shapefiles accessed here: https://www2.census.gov/geo/tiger/

[32] More information on IBTrACS can be found in Knapp et al. (2010).

[33] Population centroids use data from the 2010 Census.

[34] Accessed here:https://sedac.ciesin.columbia.edu/data/set/ulandsat-gmis-v1/data-download

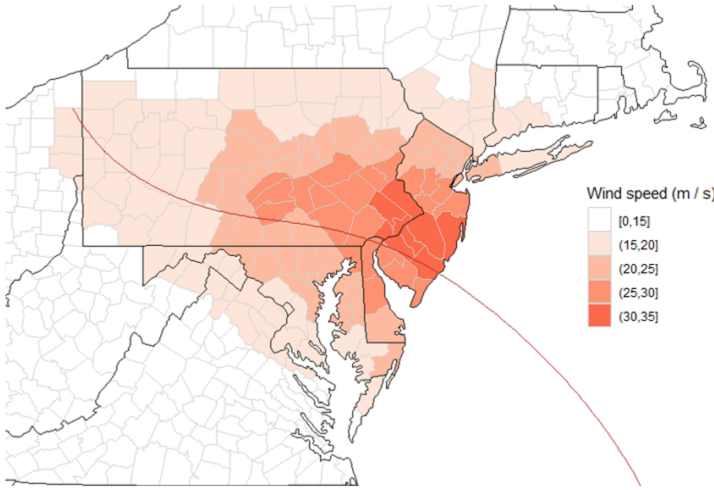

Figure 2: Output from Anderson et al. (2018) of Superstorm Sandy. Best tracks information acquired from IBTrACS.

data-set is a raster image that assigns every 30m by 30m pixel a percentage imperviousness. A pixel with a value of 0% can be thought of as containing no man-made surface that impedes the flow of water (e.g. a grass field), whereby a pixel of 100% represents a man made surface that completely impedes the flow of water (e.g. large buildings). Figure 3 provides a visualization of the GMIS data that shows the spatial variation in pixel values as well as the fine spatial resolution.

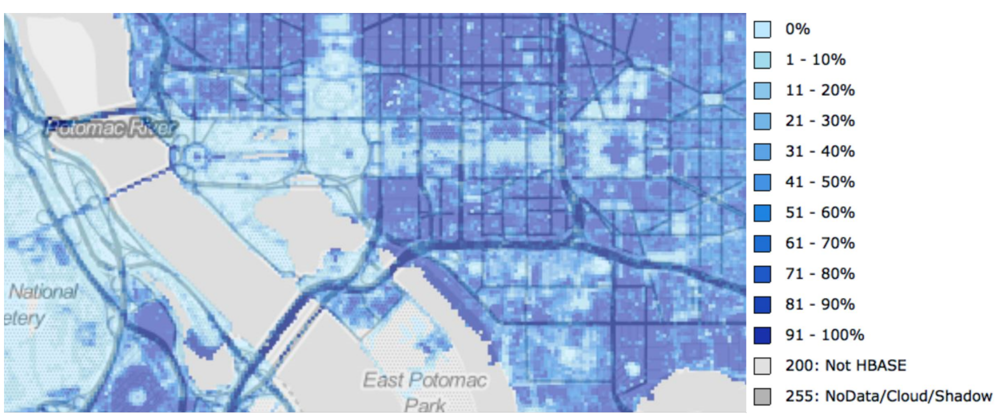

Figure 3: GMIS image of Washington D.C. in 2010. Note the data has enough spatial resolution to distinguish the Washington monument and National Mall.

The National Historic Preservation Act instructs FEMA to take special precautions when projects may have a potential impact on historic structures. To control for the possible effects of historic buildings and structures on FEMA aid, I utilized ArcGIS to sum the total number of historic buildings, structures, sites, and objects present in each county.[35]

Another major determinant of damage is storm surge from the ocean. To proxy for this I use R to construct a raster image where every pixel value is the minimum distance to the coast. I then average over all pixels falling within a county boundary. Storm surge only penetrates so far inland so I then set the value of this "distance" measurement to 40 miles for any measurements greater than 40 miles.

4.4 Information

As mentioned above the informativeness of voters can play a large role in spending decisions. After natural disasters media coverage tends to be intense and thorough. Politicians attempt to capture credit for relief spending, and voters who do not receive aid look to assign blame. Therefore, it is important to control for the informativeness of voters. To do this I follow Burgess and Besley (2002); Strömberg (2004b); Ansolabehere et al. (2006); Snyder and Strömberg (2010) and include multiple measures of information. To construct these measurements I utilize data from Nielsen. Nielsen is an information, data and measurement company that subsets the US into 210 distinct designated market areas (DMA). These DMAs are defined as areas in which the population can receive the same (or similar) television and radio station offerings. Using these maps I construct two measures of information at the county level, c:

1. Share of media market's total population that resides within a county:

$$shareDMA_c = \sum_{m \in M_c} \frac{n(c,m)}{n_m} \tag{16}$$

[35] Accessed GIS data here: https://irma.nps.gov/DataStore/Reference/Profile/2210280

2. Share of media market's population that resides within the same state, s:

$$sharestate_c = \sum_{m \in M_c} \frac{n(s,m)}{n_m} \tag{17}$$

Where $n(i,j)$ is the population that lives in locality i and j. To construct the above quantities I first create populations for each DMA-county-district triple. To do this, I utilize the Census' 5-year population estimates from 2009-2017 at the block group level. However, there are numerous instances where a DMA-county-district triple cuts through a block group. To handle these cases I use the Oak Ridge National Laboratory LandScan data-set[36] to split block groups by population. LandScan data is a raster image that maps the global population in $1km$ by $1km$ cells, which I then resample into 400 identical cells. After resampling, I find the total of all pixels that fall within each block group-DMA-district-county polygon intersection. I then mark all block groups that are "split", and assign each split a percentage based on the total share of a block group's pixels lie within each intersection. To assign a population to each intersection, the percentage is then multiplied by the Census' 5-year population estimates of the block group. After this process I am left with $n(c,d,m)$ which allows me to construct all the variables required in equations 16 and 17. While TV remains the largest source of information for voters, a rising share of information comes from the internet. In fact among voters under 49 years old the internet is already the main source of information.[37] The Federal Communications Commission (FCC) requires all internet service providers to file twice a year some basic information on how many connections per

[36]This product was made utilizing the LandScan 2000-2017™ High Resolution global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725 with the United States Department of Energy. The United States Government has certain rights in this Data Set. Neither UT-BATTELLE, LLC NOR THE UNITED STATES DEPARTMENT OF ENERGY, NOR ANY OF THEIR EMPLOYEES, MAKES ANY WARRANTY, EXPRESS OR IMPLIED, OR ASSUMES ANY LEGAL LIABILITY OR RESPONSIBILITY FOR THE ACCURACY, COMPLETENESS, OR USEFULNESS OF THE DATA SET.

[37]A survey published in 2011, [Inset pew], showed that in 2002 only 7% of respondents got their political news from the internet compared to 24% in 2010. A more recent survey in 2016 showed that 38% of respondents got their news (not only political) from the internet. Furthermore, the majority respondents under 49 stated internet was their main source of news.

1,000 households are provided with internet access of a certain speed. These filings are then made public at the census tract level. To construct relative measures for internet access I need to create internet access at the county-district level. A similar problem arises, while census tracts are small, they are split by district lines for the state congress. Again I utilize the "LandScan" method above to further disaggregate census tracts. I am left with total internet connections in every county-district tuple, $i(c, d)$ from 2009-2017. This allows me to construct two additional measures of information:

1. Total internet connections provided in a county

$$i_c = \sum_d n(c, d) \tag{18}$$

2. Share of total district internet connections in a county

$$share\ \ connections_c = \sum_{d \in c} \frac{i(c, d)}{i(d)} \tag{19}$$

4.5 Census Data

After controlling for the damage and infrastructure a county that is more "vulnerable" will value relief spending more. To control for vulnerability I utilize census data.[38] I include unemployment rate, poverty rate, income per capita, children per capita, % of population >65 years old, % of population living in an urban area, and % of population that is white. The more roads present in a county may attract more spending (i.e. more required debris removal and/or road repairs). To control for the amount of roads within a county I utilized the TIGER/Line Files produced annually by the Census Bureau from 2010-2017. Every year since 2010 the Census provides a shapefile for each county that maps all roads. I construct two measures using these data, 1) the total length of road per county and 2) the average

[38] In order to minimize the measurement error in county-level variables, and because a lot of the variables I will use do not vary much over time, I chose to utilize the Census' trailing 5-year estimates.

road density within a county.[39]

5 Empirical Strategy

The model presented in section 3.2 gave two clear empirical predictions that can be taken to the data. To remind the reader first prediction can be summarized by the following equation:

$$ln(q_{cjk}) = \beta_1 ln\big(\Psi_{cjk}\big) + \beta_2 ln(n_{cjk}) + \boldsymbol{\theta}\mathbf{X}_{cjk} + \iota_{jk} + \epsilon_{cjk} \tag{20}$$

Where Ψ_{cjk} is the average relative share of district's turnout that intersect a county, c, in the three previous state j elections prior to storm k. This is an arbitrary cut off that is meant to average out any idiosyncrasies of elections and get a more proper estimate of a counties true turnout. Let the county level controls listed in table 1 be contained in $\mathbf{X}_{cjk}$, a vector of controls that describe a counties demographics, infrastructure, damage received, swingness in previous elections, and how informed the voters are. Again, state-storm fixed effects are included, so that the variation between counties within a state after a storm is used to identify the model parameters.

The second specification provided by the model can be written as:

$$ln(q_{cjk}) = \beta_3 ln(R_{cjk}) + \beta_4 ln\big(\overline{\Psi}_{cjk}\big) + \beta_5 ln(n_{cjk}) + \boldsymbol{\theta}\mathbf{X}_{cjk} + \iota_{jk} + \epsilon_{cjk} \tag{21}$$

Where R_{cjk} is the number of representatives of county, c, in state j after storm k. And $\overline{\Psi}_{cjk} = \frac{1}{R_{cjk}}\Psi_{cjk}$ can be thought of as the average turnout share of a county.[40] The remaining terms are all identical to those described in equation 20. The appeal of this regression is that the number of representatives in a county, R_{cjk}, is measured with no measurement error.

[39] The average density is measured by applying the ArcGIS density function to each county shapefile, then averaging the resulting pixels that fall within the border of each county.

[40] Notice that this variable should be bound between 0 and 1, however because I am dividing the average share of turnout across the previous three elections by the current number of representatives a county who lost representatives can have an average turnout share greater than 1. I also did the analysis using the maximum number of representatives a county had historically (thus enforcing the bounds) and my results are not substantially different.

This specification also provides a stronger test of the data in that it predicts $\beta_3 = \beta_4 = \rho > 0$. Both regressions can be estimated via OLS with state-storm fixed effects to isolate potentially exogenous variation. However, as with most OLS estimates one must worry that results are simply driven by some omitted variable that is correlated in some systematic way with both the independent and dependent variable. In the following subsections, I present solutions that control for two major types of bias, omitted variables and selection.

5.1 Potential Omitted Variables

A set of omitted variable that would provide the most credible threat to identification would be unobserved county characteristics that are correlated with relief spending. Imagine this as some geographic characteristic that makes a county more likely to receive a marginal relief dollar. Figure 4 visually depicts this possible threat to identification. Notice that this time invariant unobservable need not be correlated with relative turnout directly, however it can influence it indirectly via relief spending in previous storms that may distort the relative voting behavior. This potential channel of relief spending influencing voter behavior has been discussed in the literature.[41]

$$\begin{tikzcd}
q_{c,t-1} \arrow[r, "corr(q_c,\Psi_c)\lesseqqgtr 0"] & \Psi_{c,t} \arrow[r] & q_{c,t} \\
& U_c \arrow[ul] \arrow[ur] &
\end{tikzcd}$$

Figure 4: Visual depiction of possible omitted variable U_c that could bias estimates.

To address this, I utilize the Census' Citizen Voting Age Population (CVAP) Special Tabulation.[42] These estimates are available at the block group level and therefore can be used to construct voting age population (VAP) at the county-district level.[43] These county-

[41] See Healy and Malhotra (2009); Chen (2013); Reeves (2011).

[42] Accessed here https://www.census.gov/programs-surveys/decennial-census/about/voting-rights/cvap.html

[43] While block groups are "split" by some district lines I utilize Landscan data to disaggregate split block groups VAP by population.

district VAP measurements allow me to construct Ψ_{cjk} and $\overline{\Psi}_{cjk}$ in equations 20 and 21 respectively. These new variables can be thought of as great instruments for the same variables constructed with turnout data, as they will not be affected by past relief spending for two reasons: 1) VAP is less likely to be manipulated by FEMA spending[44] and 2) the VAP used is much more current than the turnout in the previous three elections, thus less likely to be tainted by previous storms.

5.2 Sample Selection

The final source of bias I will discuss is that bias which is driven by selection into the sample. After a President declares a major disaster, FEMA creates a list of eligible counties. This selection process creates a possible sample selection problem.[45] To account for the sequential nature of the disaster declaration, I utilize Heckman's two step procedure for estimating consistent and unbiased estimates of determinants of PA spending. Proper implementation of this strategy calls for excluded variables (i.e. variables that show up in the first stage probit but not in the equation of interest). Implementing this strategy requires me to first estimate the selection equation:

$$Fund_{cjk} = \begin{cases} 1 & if \;\; d^*_{cjk} > 0 \\ 0 & otherwise \end{cases} \quad where \;\; d^*_{cjk} = \boldsymbol{\gamma}\mathbf{Z}_{cjk} + \nu_{cjk}$$

Where $\mathbf{Z}_{cjk}$ is a vector containing all the regressors in equation 20 plus additional variables that influence the selection of a county. I propose two excluded variables. First, I compute, for all counties being struck by at least two storms, the average rate of success.[46]

[44]This is assuming there is not some out or in migration that is caused by FEMA spending. There has been some research by Strobl (2011); Deryugina (2017) that investigate the affect hurricanes have on the demographic composition of US counties. Theses papers find weak or no evidence that large intense storms have a substantial impact on the voting age population in the short term.

[45]Husted and Nickerson (2014) use a Heckman model to correct for the FEMA declaration process at the federal to state level.

[46]A county is struck if it is within a state where a disaster is declared and it receives non-zero rainfall and/or wind gusts over 10 $\frac{m}{s}$. A county is successful if it is struck by a storm and then receives non-zero funding.

Second, I create a binary variable that indicates if heavy rainfall occurred within a county during a storm that triggered a disaster declaration. I define any rainfall total over 89 *mm* to be considered heavy. Although this threshold can vary from 50-125 *mm* without the results changing substantially. This definition comes from Meixco's Fund for Natural Disasters (FONDEN). While developed for Mexico, most of the storms in my sample occur in the southeastern region of the United States which shares the Gulf of Mexico Basin with Mexico. The results presented are robust to moving this cutoff. I got this rule from del Valle et al. (2018) who utilizes this exogenous cutoff as a regression discontinuity, to study the economic impact of disaster aid. All results that are presented in the main text use the latter excluded variable as it does not drop any observations.[47] The results are substantially the same using the restricted sample and presented in the Appendix 8.3 for reference. After obtaining estimates of $\boldsymbol{\gamma}$ by Probit, one is able to construct an estimate of the inverse mills ratio $\hat{\lambda}$ and insert it into the original regression equation as a control for the latent selection process.

$$ln(q_{cjk}) = \beta_1 ln\big(\Psi_{cjk}\big) + \beta_2 ln(n_{cjk}) + \mu\hat{\lambda}_{cjk} + \boldsymbol{\theta}\mathbf{X}_{cjk} + \iota_{jk} + u_{cjk} \tag{22}$$

5.3 Preferred Specification

To control for the sample selection and potential endogeneity caused by temporal omitted variables I will follow the estimation procedure put forth in Semykina and Wooldridge (2010). The procedure has a few requirements: 1) Z_1, a variable that affects the selection equation but not the marginal relief dollar[48]; 2) Z_2, a valid instrument for a counties relative share of historic turnout. In the following outline of the procedure let $\mathbf{X}$ and ι_{jk} be a vector of control variables and state-storm fixed effects respectively.

Procedure:

[47] Earlier storms are dropped due to lack of information on previous success.

[48] This is not necessarily a requirement, as the inverse mills ratio is technically a nonlinear function, however it is approximately linear in its range.

1. Estimate the following Probit model for each storm-state event that contains selection.[49]

$$Pr(Fund_c = 1) = \Phi\Big(\beta\Psi_c + \gamma Z_{1c} + \xi Z_{2c} + \boldsymbol{\theta}\mathbf{X}_c\Big)$$

2. Construct the inverse mills ratio, $\hat{\lambda}$, using the estimates from the Probit model.

$$\hat{\lambda} = \frac{\phi\big(\hat{\beta}\Psi_{cjk} + \hat{\gamma}Z_{1cjk} + \hat{\xi}Z_{2cjk} + \hat{\boldsymbol{\theta}}\mathbf{X}_{cjk} + \hat{\iota_{jk}}\big)}{1 - \Phi\big(\hat{\beta}\Psi_{cjk} + \hat{\gamma}Z_{1cjk} + \hat{\xi}Z_{2cjk} + \hat{\boldsymbol{\theta}}\mathbf{X}_{cjk} + \hat{\iota_{jk}}\big)}$$

3. Run a two stage least squares regression, that includes $\hat{\lambda}$ as a control, using Z_2 as an instrument for the relative share of turnout.

$$ln(q_{cjk}) = \beta_1 ln\big(\hat{\Psi}_{cjk}\big) + \beta_2 ln(n_{cjk}) + \mu\hat{\lambda}_{cjk} + \boldsymbol{\theta}\mathbf{X}_{cjk} + \iota_{jk} + \epsilon_{cjk} \text{ (2nd Stage)}$$

6 Results

Before looking at any effect of political variables it is important to discuss patterns in spending with respect to demographics, infrastructure, and perhaps most importantly damage. Table 1 presents OLS estimates from regressing FEMA spending on a litany of regressors representing a counties demographics and infrastructure, as well as exogenous measures of damage inflicted by a storm. The state-storm fixed effects restrict us to focus on variation *between* a specific state's counties *within* a single storm. Before moving on I would like to highlight a few significant results from these regressions. Specifically the positive, and statistically significant, coefficients in front of measures of damage (wind speed, average rainfall, and distance from coast) and measures of infrastructure (average imperviousness, length of road, historic buildings and "urbanness"). I take these patterns as supporting evidence that the selected controls are appropriate, and that the underlying data is valid.

[49] I define selection as state-storm pairs that pass two conditions: 1) Not all counties are granted eligibility (i.e. there is variation in the dependent variable) and 2) The selection is not perfectly predicted by the excluded variable (i.e. selection is exogenous).

VARIABLES	(1) PA (Em.)	(2) PA (Perm.)	(3) IA
Max wind speed (log)	2.23***	1.17**	1.98***
Average Rainfall (log)	0.24**	0.84***	0.56***
Km to coast (log)	-0.88***	-1.25***	-0.63**
Total Length of Road (log)	0.49***	0.68***	0.72***
# Historic Bldgs. (log)	0.09***	0.08***	-0.00
Avg. % Imperviousness	2.72***	2.06	1.36
Children per cap (log)	0.29	-0.39	-0.49
Poverty Rate	0.55	-0.84	-2.08
Income per cap (log)	0.49	0.62	-0.77
% > 65	-1.12	-1.20	-1.60
Unemployment Rate	2.22	1.03	5.98**
% White	0.34	0.66	-1.53
% Pop. in Urban Area	1.76***	0.98***	0.75***
Median Value of Housing (log)	0.08	-0.30	0.08
Median Value of Mobile Housing (log)	0.10	-0.06	-0.03
Number of Internet Conn. (log)	0.14	-0.03	0.21
% of DMA in county	0.68*	0.85**	1.19**
College Edu.	0.93	0.47	1.35
Observations	2,850	2,536	1,505
R^2	0.64	0.52	0.58
State-Storm FE	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 1: Dependent variable is the natural logarithm of FEMA aid category listed at the top of the column adjusted to 2012 USD in the Northeast region of the US.

The rest of this section will present the results produced by taking the empirical strategy described in the previous section to the data. An examination of three placebo tests will then be presented as robustness checks of the main results. The last subsection will conclude with a comparison of the results with results derived from changing the objective function of the political party to reelection of an incumbent governor (a la Strömberg (2004b)).

The first column of Tables 2 and 3 present OLS estimates of the two structural predictions produced by the first order conditions of the modeled incumbent political party. It is encouraging that the estimates in front of of the total share of turnout, Ψ are positive and lie between 0 and 1 as the model predicts. The set of estimates presented in the second column in both Tables controls for possible selection, by modeling the selection equation for each state-storm event. The coefficient in front of the Inverse Mills Ratio is not significantly different from zero, this coefficient is a direct test on the correlation between the error terms in the selection and outcome equations.

The third columns represent the results from a two stage least squares regression where I utilize the sum of the share of each districts voting age population that crosses a counties border as an instrument. The coefficient in front the instrument is 0.86 and highly significant. The coefficient in front of the relative share of turnout jumps considerably from 0.17 to 0.93. While this jump is significant, it is still falls within the bounds prescribed by the model. With this considerable of a change in the coefficient of interest, some discussion is in order. As already discussed in section 5.1 the voting age population in the current year is much less sensitive to previous county-level spending on emergency assistance. If the structure of figure 4 is what is driving this substantial change in the point estimates and you assume that $corr(q_c, U_c) > 0$ (thus attenuating the positive point estimate), then the sign of $corr(q_c, \Psi_c)$ must be negative. This relationship could be rationalized by results illustrated in Chen (2013) whereby relief spending can affect turnout depending on partisanship of the voters. Another, albeit simpler, explanation of this large positive shift could be classical measurement error, which would cause attenuation bias. State election data contains missing precincts, imputation errors, and inconsistencies that voting age population data is immune to. Additionally, the relative share of turnout is constructed using the previous *three* elections, adding a temporal dimension to the measurement error, that is not present in the contemporaneously measured census estimates of voting age population.

The last column represents results that fully account for the possible bias introduced by selection, potential omitted variables, and measurement error. The results do not differ substantially from the estimates produced in the third column, again suggesting that selection bias is not present within my sample.

The results in Table 3 require further discussion. These regressions impose a stronger test of the theoretical model because the model requires that the coefficient in front of the average share of turnout and number of representatives be an estimate of the same parameter. The F-stat reported at the bottom of each column is the result of a Wald test that $\beta_1 = \beta_2$. The emergency spending portion of the PA program provides statistically significant estimates of ρ that are similar in magnitude to the estimate in the previous regression. However, the coefficient in front of the number of representatives is significantly larger[50] than the coefficient in front of the average relative share of turnout. This difference maybe explained by classical measurement error in the average relative turnout.[51]

VARIABLES	(1) OLS	(2) Heckman	(3) IV	(4) Heckman and IV
Total Share of Turnout (log)	0.17*	0.17*	0.93***	0.95***
	(0.10)	(0.09)	(0.31)	(0.34)
Population (log)	0.45***	0.45***	-0.21	-0.22
	(0.14)	(0.12)	(0.30)	(0.33)
Inverse Mills Ratio		-0.06		-0.11
		(0.13)		(0.13)
Observations	2,842	2,842	2,842	2,842
R^2	0.66	0.66	0.46	0.46
State-Storm FE	✓	✓	✓	✓

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Dependent variable is the natural logarithm of FEMA aid category listed at the top of the column adjusted to 2012 USD in the Northeast region of the US. Swing controls include the coefficient of variation of previous three elections, how close on average the democratic vote share is to 50%. Information controls include variables on % of county with at least an associates degree, % of a media market living in a county, % of the counties media market that lives in the same state as the county, and the number of internet connections per capita in a county. Controls for damage, infrastructure, and demographics can be found in the appendix in Table 8.

[50] This is true at the 5% level but not the 1% level.

[51] Assuming that $corr(\overline{\Psi}, R) < 0$ and perhaps more strongly that all other controls are exogenous and uncorrelated with $\overline{\Psi}$ and R, then the measurement error in $\overline{\Psi}$ will attenuate β_1 and β_2. See multivariate section in Pischke (2007).

VARIABLES	(1) OLS	(2) Heckman	(3) IV	(4) Heckman and IV
Avg. Share of Turnout (log)	0.14	0.14	0.85***	0.86**
	(0.10)	(0.09)	(0.31)	(0.34)
Number of Reps. (log)	0.43***	0.43***	1.09***	1.11***
	(0.14)	(0.11)	(0.28)	(0.31)
Population (log)	0.38***		-0.21	-0.23
	(0.14)		(0.29)	(0.32)
Inverse Mills Ratio		-0.06		-0.12
		(0.13)		(0.13)
Observations	2,842		2,842	2,842
R^2	0.66	0.66	0.47	0.46
State-Storm FE	✓	✓	✓	✓

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Dependent variable is the natural logarithm of FEMA aid category listed at the top of the column adjusted to 2012 USD in the Northeast region of the US. Swing controls include the coefficient of variation of previous three elections, how close on average the democratic vote share is to 50%. Information controls include variables on % of county with at least an associates degree, % of a media market living in a county, % of the counties media market that lives in the same state as the county, and the number of internet connections per capita in a county. Controls for damage, infrastructure, and demographics can be found in the appendix in Table 9.

6.1 Robustness Checks

To give further credence to the results reported in the previous section, a series of placebo tests will be presented. Recall that the IA program spending is driven by citizens submitting applications that are then approved by federal inspectors. Conversely, the PA program application process is a collaborative effort between state and local governments and susceptible to political influences. The PA program can be split into two broad categories: 1) emergency spending that helps the local government immediately respond to the disaster damage and 2) longer term permanent spending that is used to repair (but not upgrade) existing infrastructure. Therefore, in the following regressions the IA and permanent portion of PA spending will be presented as placebo tests. The first placebo test is simply replacing the salient emergency spending from the PA program with either 1) spending from the IA program or 2) spending from the longer term component of the PA. The model predictions should not hold strongly for either program because 1) the state government should not have influence of IA spending and 2) incumbent political parties correctly expect that voters are unable to attribute long term spending to them and therefore do not use it to influence future elections. These results are presented in Table 4.

VARIABLES	(1) PA Em.	(2) PA Perm.	(3) PA Em.	(4) IA	(5) Placebo Map
Total Share of Turnout (log)					0.01
					(0.05)
Number of Reps. (log)					0.31***
					(0.09)
Population (log)	-0.22	0.18	-0.58	0.38	0.50***
	(0.33)	(0.43)	(0.52)	(0.56)	(0.09)
Inverse Mills Ratio	-0.11	-0.21	0.01	-0.09	-0.16
	(0.13)	(0.16)	(0.20)	(0.36)	(0.14)
Total Share of Turnout (log)	0.95***	0.25	1.29**	0.26	
	(0.34)	(0.47)	(0.53)	(0.57)	
Observations	2,842	2,526	2,023	1,459	2,842
R^2	0.46	0.28	0.48	0.41	0.66
State-Storm FE	✓	✓	✓	✓	✓

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Dependent variable is the natural logarithm of FEMA aid category listed at the top of the column adjusted to 2012 USD in the Northeast region of the US. Swing controls include the coefficient of variation of previous three elections, how close on average the democratic vote share is to 50%. Information controls include variables on % of county with at least an associates degree, % of a media market living in a county, % of the counties media market that lives in the same state as the county, and the number of internet connections per capita in a county. Controls for damage, infrastructure, and demographics can be found in the appendix in Table 10.

The first column is for reference and is identical to the last column in Table 2. The second column represents the same model and sample as in the first column but replaces the emergency spending of the PA program with the less salient long term PA spending. It is noteworthy that the coefficient of interest is small and very imprecisely estimated. Also, the R^2 drops significantly implying the model does a poor job at explaining variation in the long term permanent spending component of the PA program.

The third and fourth columns represent regressions run on state-storm events where both the IA and PA programs were activated. As can be seen the coefficient of interest is dramatically larger when using the emergency spending instead of the IA spending. The way in which the political parties interact with the three programs may provide reasons for these results. To begin, IA spending goes directly from the federal government to individual applicants and therefore state-level political parties influence is lessened. As per the FEMA PA program fact sheet:[52] "Recipients are responsible for managing the funds obligated to them by FEMA, including disbursement to applicants." Where "recipients" are states and "applicants" are local governments or private non-profit entities. Therefore, in the context of PA spending state-level politics are able to influence the flow of spending to counties. The last, more nuanced, point to be made is the justification for splitting the PA spending into short-term emergency spending and longer-term permanent spending. To begin, the longer term spending is used to repair roads, bridges, utilities, and parks. Also, in a country as wealthy as the United States none of these facilities would be allowed to remain in disrepair and therefore variation in this spending should be mostly explained by the damage and infrastructure of a county. In addition, these longer term projects may take up to 18 months to complete. Longer time horizons may detract from voters ability to attribute credit for these projects. Rational and sophisticated political parties realize both of these issues of salience, and therefore do not manipulate longer term spending.

The last placebo test is a simple check that spatial clustering is not driving the results. This test should help reduce the possibility that the results presented thus far are simply some artifact of physical geography. The Census Bureau provides a county-level "adjacency" matrix[53] that lists all geographic neighbors of a county. Using this, I find the share of "neighboring" turnout a county contains. This measure can be understood as a similar variable to the average shares, $\overline{\Psi}$, used in equation 21. The results of these placebo tests can be found in Table 4 column five. As with all the previous placebo tests, the estimates are not consistent with the model, implying that the main results are not driven by a spatial clustering of turnout, but in fact the political geography. To further test for spatial

[52] Accessed here:
https://www.fema.gov/media-library-data/1534520705607-3c8e6422a44db5de4885b516b183b7ce/PublicAssistanceFactSheetJune2017_Updated2018.pdf

[53] Accessed here:
https://www.census.gov/geographies/reference-files/2010/geo/county-adjacency.html

correlations, I perform a global Moran's I test on my residuals. The basic idea behind this test is to see if a counties residual[54] can be predicted by the mean residuals of neighboring counties.[55] This index can vary from 1 (strong clustering) to -1 (strong dispersion), for all the main specifications (regressions using emergency component of PA in both Tables 2 and 3) the Moran's I index ranges from 0.22-0.25 indicating a low amount of clustering.

6.2 Comparison to Strömberg (2004b)

Strömberg (2004b) studied transfers under the Federal Emergency Relief Administration (FERA). In the probabilistic voting model employed by the paper, the Governor is assumed to be the political actor of interest. The prediction of the model is that the incumbent Governor will target counties where the marginal dollar returns the highest number of voters. These counties have higher turnout rates, are better informed, and have a larger share of "swing" voters. Strömberg supports these model predictions with a detailed empirical analysis, that utilizes radio ownership as an instrument for voter information. In this study it is assumed that the ruling political party derives utility solely from gaining seats in the state legislature. However, a more realistic model would allow for a gain in party utility from winning the Gubernatorial election as well. A simple approach would be to assume that some linear combination of objective functions in this paper and Strömberg (2004b).

$$\max_{q_c} \alpha \sum_d p_d + \gamma p_g \tag{23}$$

$$\text{s.t.} \quad \sum_c q_c \leq y$$

Where α and γ are weights on winning congressional and Gubernatorial elections respectively. While a full exploration of this model is beyond the scope of this article, and left to future work, a preliminary analysis is presented here. To begin I collect county-level

[54]For counties hit multiple times, I take the average residual.

[55]I define neighbors as any county that shares a node (this includes counties that share an edge or corner).

Gubernatorial election returns for the study period from Press (2010). I then construct for each county in my sample the average turnout over the previous 3 Gubernatorial elections. I then divided this by the voting age population the year of the storm to get the turnout rate of the county. As in Strömberg (2004a) I include proxies for information[56] and swing voters[57] as well as all the demographics, controls for damage, and infrastructure included in all the previous regressions in the paper. The results for this regression are presented in Table 5.

The first two columns are simply a comparison, over the entire sample, of the separate model predictions assuming that the objective function is focused on maximizing congressional seats or gubernatorial reelection, respectively. Column three is a simple horse race between relative turnout and average turnout. As suggested in equation 23 a ruling political party may place different weights on the congressional and gubernatorial elections. I assume that parties that have "lame duck"[58] Governor's will not focus on targeting money to maximize Gubernatorial reelection but instead shift attention to maximizing the party representation in the lower house of the state congress.[59] This would be equivalent to setting $\gamma = 0$ in equation 23. Columns (4)-(7) show the results of simply running the regressions from the first two columns over the sub-sample of states that have a lame duck Governor versus those that have a Governor that will run for reelection in the future. Over the lame duck sub-sample the empirical evidence supports the model of maximizing congressional representation and rejects the model of Gubernatorial reelection, whereas the exact opposite is true when the Governor in office during the storm is running for office in the future. Unfortunately, most of the coefficients in front of the information and swingness variables are not estimated precisely enough to make any substantive claims. This preliminary results

[56] Specifically, I included the percentage of the county with at least an Associates degree, the share of a media market living in a county, and the number of internet connections per capita.

[57] To control for the presences of swing voters I include the coefficient of variation of turnout in the previous three elections and the average distance from 50-50 between the top two parties.

[58] Incumbent Governors that will not participate in the next election.

[59] Here I assume that voter's attribute FEMA aid to the candidate. Therefore any credit received by a lame duck is essentially "wasted".

VARIABLES	(1) Congress	(2) Governor	(3) Horse Race	(4) Re-Run	(5) Re-Run	(6) Lame Duck	(7) Lame Duck
Total Share of Turnout (log)	0.17*		0.19*	-0.09		0.32**	
	(0.10)		(0.10)	(0.19)		(0.13)	
Total Turnout for Gov. (log)		0.47*	0.38		0.88**		0.08
		(0.27)	(0.27)		(0.40)		(0.37)
Dist. from 50% VS_{dem}	0.16		0.13	$0.64^{\dagger}$		-0.55	
	(0.29)		(0.33)	(0.38)		(0.43)	
Coef. of Variation (log)	0.28		0.30	1.17**		-0.17	
	(0.32)		(0.31)	(0.50)		(0.37)	
Dist. from 50% VS_{dem} (Gov.)			0.13		-1.26		1.80**
			(0.71)		(0.91)		(0.76)
Coef. of Var. (Gov)			0.06		0.09		0.04
			(0.07)		(0.09)		(0.10)
Number of Internet Conn. (log)	0.11	0.14	0.13	0.15	0.24	0.03	0.03
	(0.11)	(0.11)	(0.11)	(0.17)	(0.17)	(0.15)	(0.15)
% of DMA in county	0.36	0.24	0.23	$0.86^{\dagger}$	0.94*	-0.23	-0.26
	(0.38)	(0.38)	(0.37)	(0.55)	(0.53)	(0.45)	(0.44)
College Edu.	0.85	0.91	0.91	0.60	0.76	1.07	0.89
	(0.63)	(0.65)	(0.64)	(1.06)	(1.08)	(0.85)	(0.88)
Inverse Mills Ratio	-0.03	-0.07	-0.14	-0.08	0.03	-0.06	-0.33**
	(0.11)	(0.12)	(0.12)	(0.13)	(0.14)	(0.15)	(0.16)
Observations	2,845	2,845	2,845	1,276	1,276	1,569	1,569
R^2	0.65	0.65	0.65	0.65	0.65	0.68	0.68
State-Storm FE	✓	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10, † p<0.15

Table 5: Dependent variable is the natural logarithm of FEMA aid category listed at the top of the column adjusted to 2012 USD in the Northeast region of the US. Swing controls include the coefficient of variation of previous three elections, how close on average the democratic vote share is to 50%. Information controls include variables on % of county with at least an associates degree, % of a media market living in a county, % of the counties media market that lives in the same state as the county, and the number of internet connections per capita in a county. Controls for damage, infrastructure, and demographics can be found in the appendix in Table 10.

suggest that further investigation into this model is warranted in future work.

7 Conclusion

As this current paper is closely related to Stashko (2020) it is important to compare and contrast the current results. Due to a different empirical setting Stashko (2020) does not use VAP as an instrument but instead uses it as an alternative proxy for relative vote share.

Similarly, estimates using VAP are farther from zero than those obtained using election results directly. The OLS estimate of 0.15, using election data, are strikingly similar to those reported in this paper 0.17. However, Stashko (2020) reports only a modest increase in the estimate to 0.26 when using VAP instead, while my estimates increases to 0.95. There are a few possible reasons for this rather large discrepancy. To begin,the underlying transfers being studied are different. Stashko (2020) uses intergovernmental transfers from the state to local government which are predominantly used for funding education, while not reported it can be assumed that this spending is not highly volatile and therefore a large component may simple follow a "status quo" rule determined by generations of politicians from all political parties. One of the attractive features of this study is that the funding decisions are made by the party in power at the time of the storm. If one thinks of the "status quo" component of spending as being some type of measurement error then it makes sense that the estimates from Stashko (2020) are closer to zero than those found in this paper.

This paper has presented a set of results that provide strong evidence that district maps can have a large influence on FEMA emergency spending. The preferred estimated coefficients in front of the relative share of turnout range from 0.86-0.95. To put a rough dollar amount on these estimates imagine a county that is receiving the median relief aid of \$142,509.60. If this county's share of turnout increased by 1.4 (this is the difference between the 25^{th} and 75^{th} percentiles of relative turnout in my sample) from either receiving more districts, having an increased turnout rate, or both, it would see an increase of \$160,751-\$177,567 in FEMA emergency aid. These numbers may not seem large, however when one takes into account this aid is specifically used for emergency services in the days following the storm, and that the median population of a county in my sample is 46,000 an extra \$150,000 from the federal government can go a long way in providing essential services that have a tremendous impact on citizens. For context, a 2020 report[60] from the National Highway Traffic Safety Administration's Office of Emergency Medical Services (EMS) estimated that

[60] Accessed on 8/7/2020 here: https://www.ems.gov/pdf/2020_National_EMS_Assessment.pdf

per capita spending[61] on EMS services totaled \$1.60. In the above example, a reasonable increase in relative vote share increased total spending for the median county (using median aid and median population) by roughly \$3 per capita. This paper also presents suggestive evidence that political parties are sophisticated enough to shift focus from lame duck Governor's and focus on maximizing congressional seats. Future work must be done to model the interaction between different branches of state government as political parties fight to maximize their influence at every level of government.

As the climate warms, the scientific community has warned that storms will increase in intensity, putting a larger fraction of the population at risk. As discussed in Stashko (2020) border mismatch is present in every state and is worse where gerrymandering is more extreme. Looking forward, as we approach another round of redistricting in 2022, policy makers must take into account the incentives they create when drawing new maps. This paper contributes to a growing literature that shows it is not simply "one person one vote".

[61] To get this I added state and federal funding numbers and divided by the 2019 Census estimated population of states that had data on both state and federal funding.

References

Aidt, Toke S. and Julia Shvets, "Distributive politics and electoral incentives: Evidence from seven US State legislatures," *American Economic Journal: Economic Policy*, 2012, *4* (3), 1–29.

Anderson, Brooke, Andrea Schumacher, Seth Guikema, Steven Quiring, and Joshua Ferreri, "stormwindmodel: Model Tropical Cyclone Wind Speeds," 2018.

Ansolabehere, Stephen, Alan Gerber, and James Snyder, "Equal votes, equal money: Court-ordered redistricting and public expenditures in the American States," *American Political Science Review*, 2002, *96* (4), 767–777.

_ **and James M. Snyder**, "Party control of state government and the distribution of public expenditures," *Scandinavian Journal of Economics*, 2006, *108* (4), 547–569.

_ **, Erik C. Snowberg, and James M. Snyder**, "Television and the Incumbency Advantage in U.S. Elections," 2006, *31* (4), 469–490.

_ **, James M. Snyder, and Charles Stewart**, "Old Voters, New Voters, and the Personal Vote: Using Redistricting to Measure the Incumbency Advantage," *American Journal of Political Science*, 2000, *44* (1), 17.

_ **, Maxwell Palmer, and Amanda Lee**, "Precinct-Level Election Data, 2002-2012," *Harvard Dataverse*, 2014.

Battaglini, Marco, "A dynamic theory of electoral competition," *Theoretical Economics*, 2014, *9* (2), 515–554.

Bechtel, Michael M and Jens Hainmueller, "How Lasting Is Voter Gratitude? An Analysis of the Short- and Long-Term Electoral Returns to Beneficial Policy," *American Journal of Political Science*, 2011, *55* (4), 851–867.

Berry, Christopher R., Barry C. Burden, and William G. Howell, "The President and the Distribution of Federal Spending," *American Political Science Review*, 2010, *104* (04), 783–799.

Bodet, Marc Andre, Melanee Thomas, and Charles Tessier, "Come hell or high water: An investigation of the effects of a natural disaster on a local election," 2016.

Burgess, Robin and Timothy Besley, "The Political Economy of Government Responsiveness: Theory and Evidence from India," *Quarterly Journal of Economics*, 2002, *117* (4), 1415–1451.

Chen, Jowei, "Voter Partisanship and the Effect of Distributive Spending on Political Participation," *American Journal of Political Science*, 2013, *57* (1), 200–217.

Cole, Shawn, Andrew Healy, and Eric Werker, "Do voters demand responsive governments? Evidence from Indian disaster relief," *Journal of Development Economics*, 2012, *97*, 167–181.

Cox, Gary W and Mathew D Mccubbins, "Electoral Politics as a Redistributive Game," *The Journal of Politics*, 1986, *48* (2), 370–389.

del Valle, Alejandro, Alain de Janvry, and Elisabeth Sadoulet, "Insuring Growth : Indexed Disaster Funds and Risk Response in Mexico," 2018, *30303.*

Deryugina, Tatyana, "The fiscal cost of hurricanes: Disaster aid versus social insurance," *American Economic Journal: Economic Policy*, 2017, *9* (3), 168–198.

Dixit, Avinash and John Londregan, "The Determinants of Success of Special Interests in Redistributive Politics," *The Journal of Politics*, 1996, *58* (4), 1132–1155.

Downton, Mary W and Roger A Pielke, "Discretion without accountability: Politics, flood damage, and climate," *Natural Hazards Review*, 2001, *2* (4), 157–166.

Felbermayr, Gabriel and Jasmin Gröschl, "Naturally negative: The growth effects of natural disasters," *Journal of Development Economics*, 2014, *111*, 92–106.

Garrett, Thomas A. and Russell S. Sobel, "The political economy of FEMA disaster payments," *Economic Inquiry*, 2003, *41* (3), 496–509.

Gasper, John T and Andrew Reeves, "Make It Rain? Retrospection and the Attentive Electorate in the Context of Natural Disasters," *American Journal of Political Science*, 2011, *55* (2), 340–355.

Gasper, John T. and Andrew Reeves, "Governors as Opportunists: Evidence from Disaster Declaration Requests," 2012.

Genicot, Garance, Laurent Bouton, and Micael Castanheira, "Electoral Systems and Inequalities in Government Interventions," *National Bureau of Economic Research*, 2018.

Golden, Miriam A. and Brian K. Min, "Distributive Politics Around the World," *Ssrn*, 2013.

Goodman, Doug, "Determinants of perceived gubernatorial budgetary influence among state executive budget analysts and legislative fiscal analysts," *Political Research Quarterly*, 2007, *60* (1), 43–54.

Healy, Andrew and Neil Malhotra, "Myopic voters and natural disaster policy," *American Political Science Review*, 2009, *103* (3), 387–406.

Husted, Thomas and David Nickerson, "Political Economy of Presidential Disaster Declarations and Federal Disaster Assistance," *Public Finance Review*, 2014, *42* (1), 35–57.

Ichimura, Hidehiko, "Semiparametric least squares (SLS) and weighted SLS estimation of single-index models," *Journal of Econometrics*, 1993, *58* (1-2), 71–120.

Knapp, Kenneth R., Michael C. Kruk, David H. Levinson, Howard J. Diamond, and Charles J. Neumann, "The international best track archive for climate stewardship (IBTrACS)," *Bulletin of the American Meteorological Society*, 2010, *91* (3), 363–376.

Leeson, Peter T. and Russell S. Sobel, "The Impact of FEMA on U.S. Corruption: Implications for Policy," *Ssrn*, 2009.

Levitt, Steven D. and James M. Snyder, "Political Parties and the Distribution of Federal Outlays," *Political Science*, 1995, *39* (4), 958–980.

_ **and** _ , "The impact of federal spending on house election outcomes," 1997.

Lindbeck, Assar and Jörgen W . Weibull, "Balanced-Budget Redistribution as the Outcome of Political Competition," *Public Choice*, 1987, *52* (3), 273–297.

Moser, Christine, "Poverty reduction, patronage, or vote buying? The allocation of public goods and the 2001 election in Madagascar," *Economic Development and Cultural Change*, 2008, *57* (1), 137–162.

Myatt, David P, "A Theory of Voter Turnout," 2015.

Persson, Torsten and Guido Tabellini, "The size and scope of government: Comparative politics with rational politicians," *European Economic Review*, 1999, *43* (4-6), 699–735.

Pischke, S, "Lecture Notes on Measurement Error," 2007.

Press, Congressional Quarterly, "CQ Press Voting and Elections Collection," *Online, http://library.cqpress. com/elections*, 2010.

Reeves, Andrew, "Political Disaster: Unilateral Powers, Electoral Incentives, and Presidential Disaster," *The Journal of Politics*, 2011, *73* (4), 1142–1151.

Robinson, P. M., "Root-N-Consistent Semi-parametric Regression," *Econometrica*, 1988, *56* (4), 931–954.

Salkowe, Richard S and Jayajit Chakraborty, "Federal Disaster Relief in the U.S.: The Role of Political Partisanship and Preference in Presidential Disaster Declarations and Turndowns," *Journal of Homeland Security and Emergency Management*, 2009, *6* (1).

Semykina, Anastasia and Jeffrey M. Wooldridge, "Estimating panel data models in the presence of endogeneity and selection," *Journal of Econometrics*, 2010, *157* (2), 375–380.

Snyder, James M. and David Strömberg, "Press Coverage and Political Accountability," *Journal of Political Economy*, 2010, *118* (2), 355–408.

Sobel, Russell S, Christopher J Coyne, and Peter T Leeson, "The Political Economy of FEMA: Did Reorganization Matter ?," *Journal of Public Finance and Public Choice*, 2007, *17* (2/3), 49–65.

Stashko, Allison, "Crossing the District Line : Border Mismatch and Targeted Redistribution," 2020.

Strobl, Eric, "The economic growth impact of hurricanes: Evidence from U.S. coastal counties," *Review of Economics and Statistics*, 2011, *93* (2), 575–589.

Strömberg, David, "Mass Media Competition , Political Competition , and Public Policy," *The Review of Economic Studies*, 2004, *71* (1), 265–284.

_ , "Radio's Impact on Public Spending," *Quarterly Journal of Economics*, 2004, *119* (1), 189–221.

_ , "How the Electoral College Influences Campaigns and Policy: The Probability of Being Florida," *The American Economic Review*, 2008, *98* (3), 769–807.

Sylves, R. and Z. I. Buzas, "Presidential Disaster Declaration Decisions, 1953-2003: What Influences Odds of Approval?," *State and Local Government Review*, 2007, *39* (1), 3–15.

Thompson, Joel A., "Bringing Home the Bacon: The Politics of Pork Barrel in the North Carolina Legislature," *Legislative Studies Quarterly*, 1986, *11* (1), 91.

_ **and Gary F. Moncrief**, "Pursuing the Pork in a State Legislature: A Research Note," *Legislative Studies Quarterly*, 1988, *13* (3), 393–401.

Willoughby, Huch, R.W.R. Darling, and M.E. Rahn, "Parametric Representation of the Primary Hurricane Vortex . Part II : A New Family of Sectionally Continuous Profiles," *Monthly Weather Review*, 2006, *134*, 1102–1120.

Xia, Youlong, Kenneth Mitchell, Michael Ek, Justin Sheffield, Brian Cosgrove, Eric Wood, Lifeng Luo, Charles Alonge, Helin Wei, Jesse Meng, Ben Livneh, Dennis Lettenmaier, Victor Koren, Qingyun Duan, Kingtse Mo, Yun Fan, and David Mocko, "Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products," *Journal of Geophysical Research: Atmospheres*, 2012, *117* (D3), 1–27.

8 Appendix

8.1 Semiparametric Selection Correction

In the paper I utilized a Heckman style selection model. In this model it is assumed that the errors in the selection and outcome equation are jointly normal. If this assumption fails my results may suffer from misspecification error. Semi-parametric methods give us the ability to correct for selection without making distributional assumptions. I will present in this subsection the results from a semi-parametric selection model. The procedure for this model is as follows:

1. First demean all independent variables, $\mathbf{Z}$[62], and an indicator of funded vs non-funded counties, $Fund$, using the state-storm means.

$$\tilde{\mathbf{Z}}_{\mathbf{cjk}} = \mathbf{Z}_{\mathbf{cjk}} - \overline{\mathbf{Z}}_{\mathbf{jk}}$$

$$F\tilde{und}_{cjk} = Fund_{cjk} - \overline{Fund}_{jk}$$

2. Run the semi-parametric least squares procedure put forth in Ichimura (1993) and collect the residuals, $\hat{\epsilon}_{cjk}$.

$$F\tilde{und}_{cjk} = \tau\left(\tilde{\mathbf{Z}}\gamma\right) + \epsilon_{cjk}$$

3. Allow these residuals, which represent information on the selection process, enter non-parametrically, via some unknown function $g(\ )$, into the outcome equation as described in Robinson (1988). Allow all variables of interest and controls be included in the vector $\mathbf{X}$.

$$ln(q_{cjk}) = \boldsymbol{\beta}\mathbf{X}_{cjk} + \mu g(\hat{\epsilon}_{cjk}) + +\iota_{jk} + u_{cjk}$$

[62] For simplicity assume that the vector $\mathbf{Z}$ contains the variables of interest, (Ψ, n) as well as the excluded heavy rain threshold variable.

The attractiveness of this procedure is that it makes no distributional assumptions about the errors in the selection and outcome equations. As the results report in Table 6 below show, this procedure does not substantially change the results presented in the main body of the text.[63] Thus for simplicity and expositional purposes, I prefer to present the results obtained via the more traditional, Heckman method.

VARIABLES	(1) Ichimura-Robinson	(2) Ichimura-Robinson
Total Share of Turnout (log)	0.26**	
	(0.11)	
Avg. Share of Turnout (log)		0.18*
		(0.09)
Number of Reps. (log)		0.45***
		(0.14)
Population (log)	0.44***	0.39***
	(0.14)	(0.12)
Observations	2,842	2,840
R^2	0.59	0.58
State-Storm FE	✓	✓

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Dependent variable is the natural logarithm of FEMA aid category listed at the top of the column adjusted to 2012 USD in the Northeast region of the US. Swing controls include the coefficient of variation of previous three elections, how close on average the democratic vote share is to 50%. Information controls include variables on % of county with at least an associates degree, % of a media market living in a county, % of the counties media market that lives in the same state as the county, and the number of internet connections per capita in a county. Controls for damage, infrastructure, and demographics can be found in the appendix in Table **??**.

8.2 Robustness to Leave One Out

To test that no single disaster or state is driving my results I iteratively drop a state or storm and re-estimate my results. Figure 5 visualizes the coefficients that come from this process. The graphs on the left panels represent the results from running OLS with state-storm fixed effects and errors clustered at the state-storm level. The graphs on the right represent the results from the preferred specification, with bootstrapped standard errors.

[63]There does seem to be a significant bump in the estimated coefficient in front the total share of turnout. This suggests is that the normality assumption of the Heckman procedure may not be hold, however it is not large enough to warrant a sizable discussion.

The results remain stable and significantly positive for all 282 (2 models with 124 storms and 17 states) iterations, except for when I drop Louisiana in the OLS estimation[64]

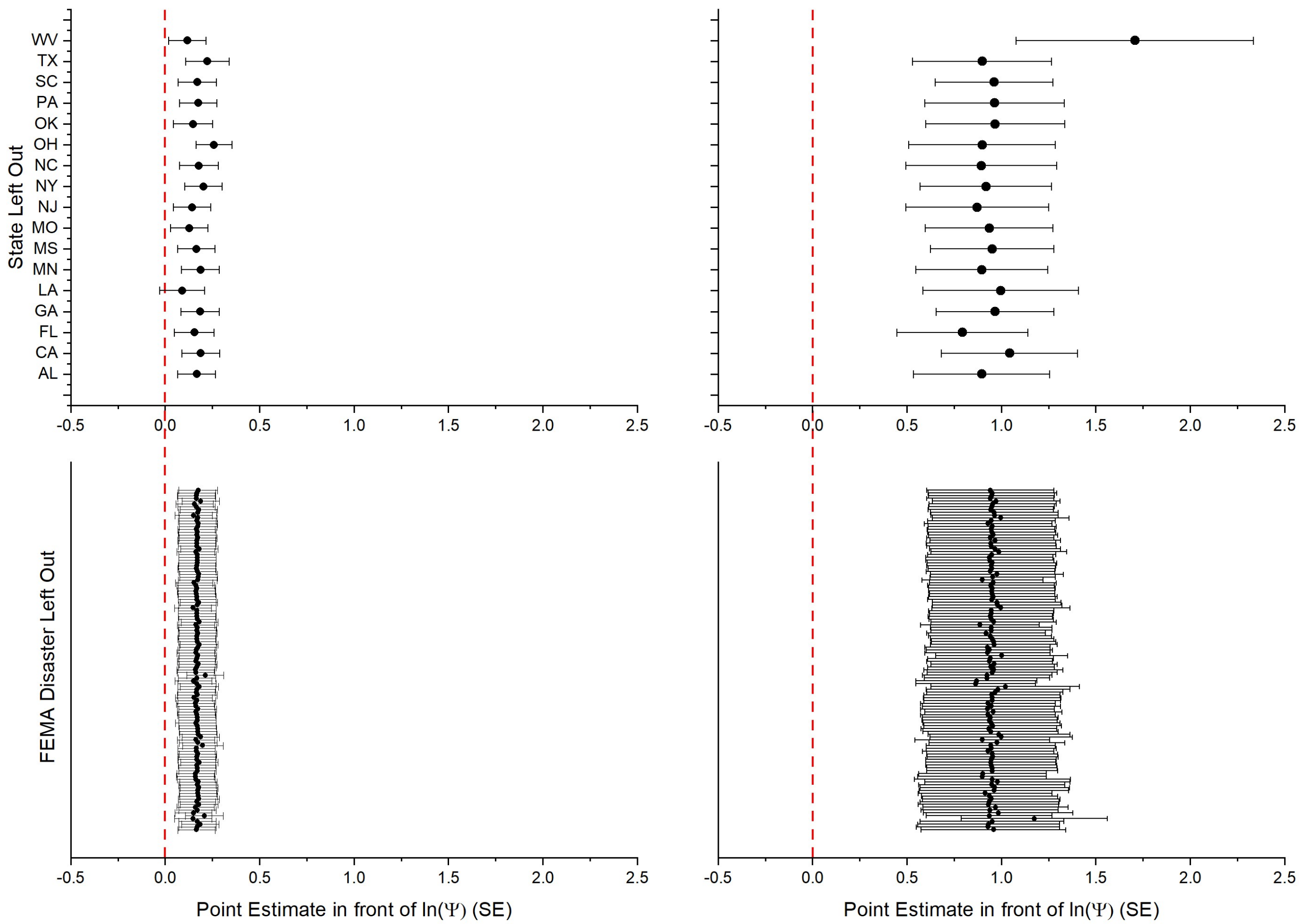

Figure 5: Top Left: OLS results after iteratively dropping a state; Top Left: IV + Heckman results after iteratively dropping a state; Bottom Left: OLS results after iteratively dropping a disaster; Bottom Right: IV + Heckman results after iteratively dropping a disaster

8.3 Alternate Excluded Variable

The results obtained when using the previous success rate of securing PA funding rate are presented here. Table 7 is structured in the same way as Table 13. The OLS estimates

[64]The estimate is still significant at the 10% level so I do not take this as a significant concern. Additionally, the estimate not using Louisiana observations does not exhibit this decrease when using the preferred empirical specification.

are quite a bit higher due to the change in the sample to more current storms. However, the coefficient moves in the same direction after controlling for selection (second column) and possible endogenity (third column). The preferred specification in the fourth column produces a similar point estimate as in the main text, further supporting the main results.

VARIABLES	(1) OLS	(2) Heckman	(3) IV	(4) Heckman and IV
Total Share of Turnout (log)	0.32***	0.32***	0.83***	0.85***
	(0.11)	(0.11)	(0.28)	(0.33)
Population (log)	0.34**	0.34**	-0.12	-0.13
	(0.14)	(0.13)	(0.28)	(0.32)
Inverse Mills Ratio		-0.15		-0.15
		(0.15)		(0.17)
Observations	2,471	2,471	2,471	2,471
R^2	0.66	0.66	0.48	0.48
State-Storm FE	✓	✓	✓	✓

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Dependent variable is the natural logarithm of FEMA Public Assistance emergency spending adjusted to 2012 USD in the Northeast region of the US. Swing controls include the coefficient of variation of previous three elections, how close on average the democratic vote share is to 50%. Information controls include variables on % of county with at least an associates degree, % of a media market living in a county, % of the counties media market that lives in the same state as the county, and the number of internet connections per capita in a county.

8.4 Tables of Controls

This section contains tables of all the controls for each regression.

VARIABLES	(1) OLS	(2) Heckman	(3) IV	(4) Heckman and IV
Dist. from 50% VS_{dem}	0.15	0.15	0.19	0.20
Coef. of Variation (log)	0.28	0.28	0.54	0.54
% of Reps. that are Dems	0.05**	0.05***	0.03	0.03
Children per cap (log)	0.10	0.11	0.05	0.06
Total Length of Road (log)	-0.09	-0.09	-0.10	-0.10
Poverty Rate	0.98	0.97	0.77	0.75
Income per cap (log)	0.50	0.49	0.37	0.36
Median Value of Housing (log)	-0.31	-0.31*	-0.28	-0.28
Median Value of Mobile Housing (log)	0.18**	0.19**	0.16*	0.16*
% > 65	-0.41	-0.38	-1.02	-0.99
Unemployment Rate	1.30	1.31	1.30	1.33
% White	0.44	0.44	0.50	0.51
# Historic Bldgs. (log)	0.06***	0.06***	0.06***	0.06***
Avg. % Imperviousness	-1.35	-1.35	-1.27	-1.27
% Pop. in Urban Area	0.79***	0.80***	0.72***	0.73***
Max wind speed (log)	2.22***	2.22***	2.21***	2.20***
Average Rainfall (log)	0.22*	0.21***	0.21*	0.21
Km to coast (log)	-1.12***	-1.12***	-1.04***	-1.03***
Number of Internet Conn. (log)	0.09	0.08	0.10	0.10
% of DMA in county	0.32	0.31	0.35	0.34
College Edu.	0.84	0.84	0.83	0.82
Observations	2,842	2,842	2,842	2,842
R^2	0.66	0.66	0.46	0.46

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: This is the set of controls for Table 2. Dependent variable is the natural logarithm of FEMA aid category listed at the top of the column adjusted to 2012 USD in the Northeast region of the US. State-storm fixed effects are included to focus on variation between counties within a state following a specific storm.

VARIABLES	(1) OLS	(2) Heckman	(3) IV	(4) Heckman and IV
Dist. from 50% VS_{dem}	0.12	0.12	0.16	0.17
Coef. of Variation (log)	0.25	0.25	0.49	0.49
% of Reps. that are Dems	0.03	0.03*	0.01	0.01
Children per cap (log)	0.09	0.09	0.05	0.05
Total Length of Road (log)	-0.12	-0.12	-0.12	-0.12
Poverty Rate	1.02	1.01	0.82	0.80
Income per cap (log)	0.51	0.51	0.39	0.38
Median Value of Housing (log)	-0.33	-0.33*	-0.30	-0.30
Median Value of Mobile Housing (log)	0.20***	0.21**	0.18**	0.18**
% > 65	-0.30	-0.28	-0.88	-0.85
Unemployment Rate	1.64	1.65	1.59	1.60
% White	0.53	0.54*	0.58	0.59
# Historic Bldgs. (log)	0.06***	0.06***	0.05***	0.05***
Avg. % Imperviousness	-1.39	-1.39	-1.31	-1.31
% Pop. in Urban Area	0.84***	0.85***	0.77***	0.78***
Max wind speed (log)	2.21***	2.20***	2.19***	2.18***
Average Rainfall (log)	0.22*	0.22***	0.21*	0.21
Km to coast (log)	-1.10***	-1.10***	-1.03***	-1.03***
Number of Internet Conn. (log)	0.00	-0.00	0.03	0.02
% of DMA in county	0.60	0.60*	0.58	0.57
College Edu.	0.83	0.83	0.82	0.81
Observations	2,842	2,842	2,842	2,842
R^2	0.66	0.66	0.47	0.46

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9: This is the set of controls for Table 3. Dependent variable is the natural logarithm of FEMA aid category listed at the top of the column adjusted to 2012 USD in the Northeast region of the US. State-storm fixed effects are included to focus on variation between counties within a state following a specific storm.

VARIABLES	(1) PA Em.	(2) PA Perm.	(3) PA Em.	(4) IA	(5) Placebo Maps
Dist. from 50% VS_{dem}	0.20	1.05***	0.40	0.86*	0.12
Coef. of Variation (log)	0.54	0.28	0.76	0.29	0.19
% of Reps. that are Dems	0.03	0.03	0.04	0.03	0.03**
Children per cap (log)	0.06	-0.57*	-0.22	-0.58	0.11
Total Length of Road (log)	-0.10	0.31*	-0.04	0.14	-0.12
Poverty Rate	0.75	-0.85	0.41	-1.31	1.02
Income per cap (log)	0.36	0.46	0.20	-0.88	0.52
Median Value of Housing (log)	-0.28	-0.52**	-0.19	-0.15	-0.33*
Median Value of Mobile Housing (log)	0.16*	-0.01	0.17	0.02	0.21***
% > 65	-0.99	-0.66	-2.43	-1.32	-0.15
Unemployment Rate	1.33	0.12	2.43	5.27*	1.67
% White	0.51	0.77	0.77	-1.20	0.53*
# Historic Bldgs. (log)	0.06***	0.06***	0.07***	-0.04	0.06***
Avg. % Imperviousness	-1.27	-0.71	-1.91	-2.08	-1.39
% Pop. in Urban Area	0.73***	0.40	0.80**	-0.20	0.87***
Max wind speed (log)	2.20***	1.14*	2.20***	1.97***	2.20***
Average Rainfall (log)	0.21	0.85***	0.22	0.52	0.22***
Km to coast (log)	-1.03***	-1.43***	-0.87***	-0.88***	-1.11***
Number of Internet Conn. (log)	0.10	-0.09	0.23*	0.13	-0.01
% of DMA in county	0.34	0.54	0.36	0.76	0.58*
College Edu.	0.82	0.44	0.42	1.32	0.82
Observations	2,842	2,526	2,023	1,459	2,842
R^2	0.46	0.28	0.48	0.41	0.66

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10: This is the set of controls for Table 4. Dependent variable is the natural logarithm of FEMA aid category listed at the top of the column adjusted to 2012 USD in the Northeast region of the US. State-storm fixed effects are included to focus on variation between counties within a state following a specific storm.

VARIABLES	(1) Congress	(2) Governor	(3) Horse Race	(4) Re-Run	(5) Re-Run	(6) Lame Duck	(7) Lame Duck
% of Reps. that are Dems	0.05**			0.07**		0.03	
Children per cap (log)	0.18	0.14	0.14	0.05	0.00	0.20	0.12
Total Length of Road (log)	-0.09	-0.04	-0.05	-0.07	0.03	-0.16	-0.11
Poverty Rate	0.98	1.49	1.33	-0.07	0.76	1.61	1.64
Income per cap (log)	0.41	0.24	0.24	0.70	0.25	0.11	-0.03
Median Value of Housing (log)	-0.18	-0.11	-0.12	-0.33	-0.13	0.06	0.10
% > 65	-0.32	-1.07	-1.08	0.66	-1.04	-1.07	-1.03
Unemployment Rate	1.38	1.40	1.37	1.75	1.87	1.64	1.30
% White	0.51	0.47	0.49	0.01	0.12	0.68	0.35
# Historic Bldgs. (log)	0.07***	0.07***	0.06***	0.02	0.02	0.10***	0.11***
Avg. % Imperviousness	-1.27	-0.28	-0.40	-1.90	0.15	-1.24	-0.51
% Pop. in Urban Area	0.73***	0.72***	0.72***	1.26***	1.15***	0.03	0.04
Max wind speed (log)	2.21***	2.23***	2.21***	1.82***	1.85***	2.73***	2.77***
Average Rainfall (log)	0.22*	0.21*	0.21*	0.17***	0.17***	0.56***	0.56***
Km to coast (log)	-1.10***	-1.10***	-1.09***	-1.15***	-0.98**	-1.18***	-1.33***
Observations	2,845	2,845	2,845	1,276	1,276	1,569	1,569
R^2	0.65	0.65	0.65	0.65	0.65	0.68	0.68

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11: This is the set of controls for Table 5. Dependent variable is the natural logarithm of FEMA aid category listed at the top of the column adjusted to 2012 USD in the Northeast region of the US. State-storm fixed effects are included to focus on variation between counties within a state following a specific storm.