Ashoka University
Economics Discussion Paper 162

Do Politics Shape Economic Recovery through Federal Disaster Assistance?

April 2026

Parush Arora, Ashoka University
Yash Khaitan, Ashoka University
Derek Tran, Upstart Inc.

https://ashoka.edu.in/economics-discussionpapers

Do Politics Shape Economic Recovery through Federal Disaster Assistance?

Parush Arora[1], Yash Khaitan[1] and Derek Tran[2]

Abstract

This paper investigates the causal impact of FEMA grants and SBA loans on post-disaster economic recovery in U.S. counties over 2003–2021. While natural disasters cause less than 0.1% of annual US GDP, they have significant localized economic impacts, reaching 2% or more in one in twenty affected counties. We find that a $1 increase in disaster aid generates $1.79–$1.98 in local GDP growth in the following year. Our identification strategy relies on an instrument based on county-level political competition (vote margin). For the exogeneity condition, we rely on the winner-take-all electoral system, where presidential outcomes are effectively predetermined at the state level unless the state is a swing state. Thus, in the non-swing states, politicians' incentive to improve local economic conditions is eliminated. We confirm this by finding a significant effect of political competition on counties' GDP growth in swing states but an insignificant and near-zero effect for non-swing states. In the first stage of 2SLS, we find the instrument to be relevant as it significantly affects the allocation of aid between counties. Interestingly, we also find that this effect is stronger when the disaster occurs closer to an election (state or federal). Our results suggest that disaster aid is an effective short-run fiscal stimulus with no significant effects beyond one year.

Keywords: Fiscal Policy, Natural Disasters, Federal Aid, FEMA, SBA, Economic Recovery
JEL Codes: R11, R15, Q54, Q58, H84

[1]Department of Economics, Ashoka University.
[2]Upstart Inc., United States

1 Introduction

Natural disasters cause approximately 12 billion dollars in damage to the United States every year. Although the economic toll of natural disasters constitutes less than 0.1% of the US's annual Gross Domestic Product (GDP), one in twenty events has a local GDP impact of 2% or more within affected jurisdictions.[1] Climate change has also exacerbated the effects of disasters, with damages increasing around 5.6% per year since 2000 and real disaster costs growing faster than GDP (Deryugina [2017]). To help impacted parties recover from these disasters, the Federal Emergency Management Agency (FEMA) provides grants while the Small Business Administration (SBA) offers low-interest disaster loans. This federal aid, on average, amounts to 23.4% of the recorded yearly damages, which is approximately $4 billion[2]. Given the size of the disaster aid program, it is important to understand its effect on GDP recovery and whether the benefits justify the cost.

Our paper investigates how FEMA grants and low-interest rate loans by the SBA affect GDP recovery at the county-level post-disaster. We find that, conditional on being affected by a disaster, counties that receive federal aid grew faster in the following calendar year than counties that did not receive aid. We believe that the timing of our paper is appropriate given the current political scenario. Since early 2025, there have been reports that approximately 2000 employees left FEMA through terminations or voluntary departures. $11 billion in disaster reimbursements to 45 states were postponed from FY2025 to FY2026[3]. In April 2025, the government ended, the Building Resilient Infrastructure and Communities (BRIC) program, one of FEMA's grant programs[4]. Recently, FY2026 budget proposes a $646 million cut to FEMA[5]. The ongoing reforms to FEMA underscore the need for rigorous evidence on the effectiveness of such aid. This paper contributes to that evidence base with the aim of informing future policy design.

Our analysis needs to account for potential confounding factors that could affect GDP and federal aid. Ideally, if federal aid were randomly distributed among disaster-affected counties, a TWFE model would have identified the average treatment effect. However, the decision made by FEMA or SBA to grant federal aid is accomplished through an internal selection criterion. In

[1] 2% is chosen as the cutoff point since it is the benchmark for a recession set out by the IMF. When looking at severe recession, defined as a 5% impact to local GDP, this figure represents 1.8% of all counties.

[2] On annual average, SBA loans amounted to 2.34 billion whereas FEMA aid amounted to 1.62 billion from 2003 to 2021.

[3] Source: Disaster Relief Fund: Monthly Report (September)

[4] https://www.congress.gov/crs-product/IN12609

[5] https://www.whitehouse.gov/omb/information-resources/budget/the-presidents-fy-2026-discretionary-budget-request/

addition to the amount of damages caused by the disaster, there are other factors that can affect the allocation decision. Using the two-way fixed-effects (TWFE) model, we find that the effect of federal aid quantity on GDP recovery is statistically insignificant. We believe that the Average Treatment Effect on the Treated (ATT) from TWFE model is biased due to the reasons discussed above. The FEMA selection criteria allocate the aid in proportion to the damage caused by natural disasters to the county. Thus, selection bias may cancel the federal aid's recovery effect, attenuating the estimated effect toward zero since counties with more severe damage receive more aid but also face slower counterfactual recovery.

To deal with endogeneity, we estimate the causal effect using an instrumental variable (IV) approach with county and time fixed effects. We construct a novel instrument for federal aid using county-level vote margins, restricting the sample to non-swing states where this variation is plausibly exogenous to local GDP. We argue that swing counties in non-swing states affect GDP growth only through the higher likelihood of receiving federal aid.

For the exogeneity condition, we argue that this instrument is exogenous in non-swing states. Even though economic theory predicts a positive association between political competition and economic outcomes, we argue that the incentive for politicians to perform better disappears in a non-swing state. This is due to the presidential election setup in the US states, where the winning candidate receives all of the state's electoral votes. The political competition among counties should not affect the candidate's behavior in non-swing states since the dominant party's candidate is expected to take the office irrespective of how the county votes. In swing states, by contrast, additional effort in a competitive county can shift the statewide outcome at the margin, creating incentives for targeted economic delivery. We find evidence consistent with this hypothesis and find a significant positive association between GDP growth rate and political competition among counties in swing states, but no significant evidence for non-swing states.

In the first stage, we find that, within non-swing states, swing counties are more likely to receive larger aid allocations, satisfying the relevance condition. We find the effect to be stronger when the disaster timing is closer to the election cycle and strongest a quarter before the election. Interestingly, this effect disappears in the swing states. A potential explanation may be the difference in the election strategy between swing and non-swing states. It is plausible that non-swing states disproportionately distribute the federal aid to swing counties to gain their favor for elections, whereas swing states follow a uniform strategy with regard to distributing federal aid.

In the second stage, we find that a 1% increase in federal aid, on average, results in a 5.3 basis point increase in the local GDP growth rate for the next calendar year. This translates to a return of \$1.79–\$1.98 for every dollar spent on federal aid. However, we find no evidence that federal aid affects GDP recovery beyond the year following the disaster.

We contribute to three strands of research. First, we are the first to estimate the causal effect of federal aid on the recovery of counties following a natural disaster. Generally, the literature in this field only looks at the firm and household-level (Billings et al. [2019]) without considering the effect on the aggregate economy of the affected county. For example, Davlasheridze and Geylani [2017] show that small businesses have a higher chance of survival when a local region is provided with disaster loans. In contrast, evidence from Kousky et al. [2018] shows that individuals reduce insurance purchases if they receive a disaster relief loan. Watson et al. [2021] find that businesses approved for the SBA loan had 2.8–3.9 times higher likelihood of surviving a hurricane than businesses that do not receive disaster relief loans. Davlasheridze and Geylani [2017] find that for every additional dollar per business spent on disaster loans, four small businesses survive.

Second, we contribute to the literature on how political competition affects welfare, which is sparsely explored from an empirical point of view. In our process of building an IV, we discover that the positive association between political competition and GDP growth holds only in swing states (the association is significant and Four times as large as the corresponding estimate for non-swing states.), consistent with the winner-take-all electoral system that lowers incentives for local performance in non-swing states. Besley et al. [2010] develop a theoretical model showing that insufficient political competition leads to anti-growth policies such as higher taxes and reduced capital spending. Their empirical analysis of US state panel data confirms a strong link between low political competition and low income growth. Ma and McLaren [2018] empirically show that the US tariff structure favors industries located in swing states, estimating that voters in non-swing states are valued at only 77% of their swing state counterparts. While this literature has focused on state-level outcomes or specific policy domains like tariffs, we extend it by analyzing the effect of political competition on GDP growth at the county-level.

Third, we find evidence that political competition affects federal aid distribution at the county-level. Although previous research found evidence that political factors play a role in the allocation of aid at the state level (Garrett and Sobel [2003], Stramp [2013]), we are the first to document that this factor is relevant at the county-level as well. Interestingly, we find that the effect is significant only when the county belongs to a non-swing state. A potential new insight is that non-swing states target electorally competitive counties, whereas swing states uniformly focus on all the counties. A thorough investigation of the mechanism is outside the scope of the paper and we leave it as a topic for future research.

The remainder of the paper is organized as follows. In the next section, we describe the institutional background with respect to FEMA and discuss related literature. Section 3 discusses the data. Section 4 presents the baseline results and instrumental variable analysis. Section 5 concludes the paper.

2 Background

2.1 Institutional Background

The framework for Federal Disaster Assistance was established by the Robert T. Stafford Act of 1988. When a disaster occurs and its magnitude exceeds the response capacity of the state and local governments, the disaster declaration process is initiated by a formal request from the state governor to the president. Prior to this, the governor must have activated the state emergency plan and ensured that local response efforts are underway (Beauchesne [2001]). Following the request, FEMA assesses the scale of the damage and advises the president on whether a federal disaster declaration is warranted. The president may then issue an emergency declaration, a major disaster declaration, or decline the request. Once a declaration is approved, FEMA administers assistance through the Disaster Relief Fund (DRF) and coordinates the broader federal response.[6]

Each type of presidential declaration activates a different set of federal funding mechanisms. *Emergency declarations* authorize federal funding only up to $5 million, as they are intended for incidents that require immediate federal assistance but are limited in scope and duration. In contrast, *major disaster declarations* activate an array of FEMA programs under the Disaster Relief fund, such as the Public Assistance (PA), Hazard Mitigation Grant Program (HMGP), and Individual Assistance (IA) programs, each of which targets a different phase of recovery. Public Assistance (PA) provides grants to state and local governments, as well as eligible non-profit organizations, to cover the costs of debris removal, emergency protective measures, and the repair or reconstruction of damaged public infrastructure, such as roads, utilities, schools, and hospitals. Hazard Mitigation Grant Program (HMGP) funds projects aimed at reducing future disaster risk, thereby strengthening long-term community resilience. Individual Assistance (IA), in contrast, delivers direct financial support to households and individuals through FEMA's Individuals and Households Program (IHP), which provides grants for temporary housing,

[6] See Figure A.8 in the Appendix for a schematic of the full declaration process

home repair, and other disaster-related expenses not covered by insurance.[7]

Complementing FEMA's Individual Assistance (IA) programs, the Small Business Administration (SBA) provides low-interest disaster loans to homeowners, renters, and businesses to repair or replace uninsured property losses. Although the SBA's disaster loan program is frequently activated in parallel with FEMA following a presidential disaster declaration, the agency also holds independent authority to issue its own disaster declarations.[8] This paper focuses specifically on the support provided through the FEMA IA, FEMA PA, and SBA disaster loan components of Federal funding under major disaster declarations. These channels are particularly relevant for analyzing short to medium-term economic recovery at the county-level, as they involve direct cash transfers to households and businesses.

FEMA PA is distributed to state and local governments for infrastructure repair or mitigation projects whereas FEMA IA is allocated to individuals. Individuals and firms must apply for assistance, demonstrate eligibility, and undergo a federal verification process. Under IHP, FEMA verifies each applicant's identity, occupancy, and insurance coverage before assigning inspectors to conduct on-site or remote assessments of property damage. Based on these inspections, FEMA determines eligibility and grant amounts, which typically cover temporary housing, home repairs, and essential expenses not compensated by insurance. Applicants receive a formal determination letter detailing approved assistance or reasons for denial, and may appeal decisions or submit additional documentation.

In parallel, the SBA processes disaster loan applications from homeowners, renters, and businesses. The SBA assesses creditworthiness, verifies property losses through its own inspectors, and determines loan amounts according to uninsured damages. The approved loans are then disbursed directly to the applicants, often in multiple installments as reconstruction progresses. FEMA and SBA coordinate closely throughout this process to prevent duplication of benefits, ensuring that grants and loans compensate for different portions of verified losses.

Even though the internal criteria that affect the distribution of aid are unknown to the public, some of the prominent factors can be identified through the data. To contextualize, Figure 1 presents the distribution of a few county-specific factors by aid status—whether a county received non-zero federal aid or not post-disaster. Panel (a) plots the distribution of the log of damages where on average, counties with higher damage are more likely to receive federal

[7] IA consists of multiple sub-programs, of which IHP is the largest and most significant component. The other components of IHP include Disaster Unemployment Assistance (DUA), Crisis Counselling and Training Program (CCP), Disaster Legal Services (DLS), Disaster Case Management (DCM), and Voluntary Agency Coordination (VAC). (https://www.fema.gov/sites/default/files/documents/fema_iappg-1.1.pdf)

[8] One can find the details about SBA's loan eligibility criteria at https://www.congress.gov/crs-product/R44412

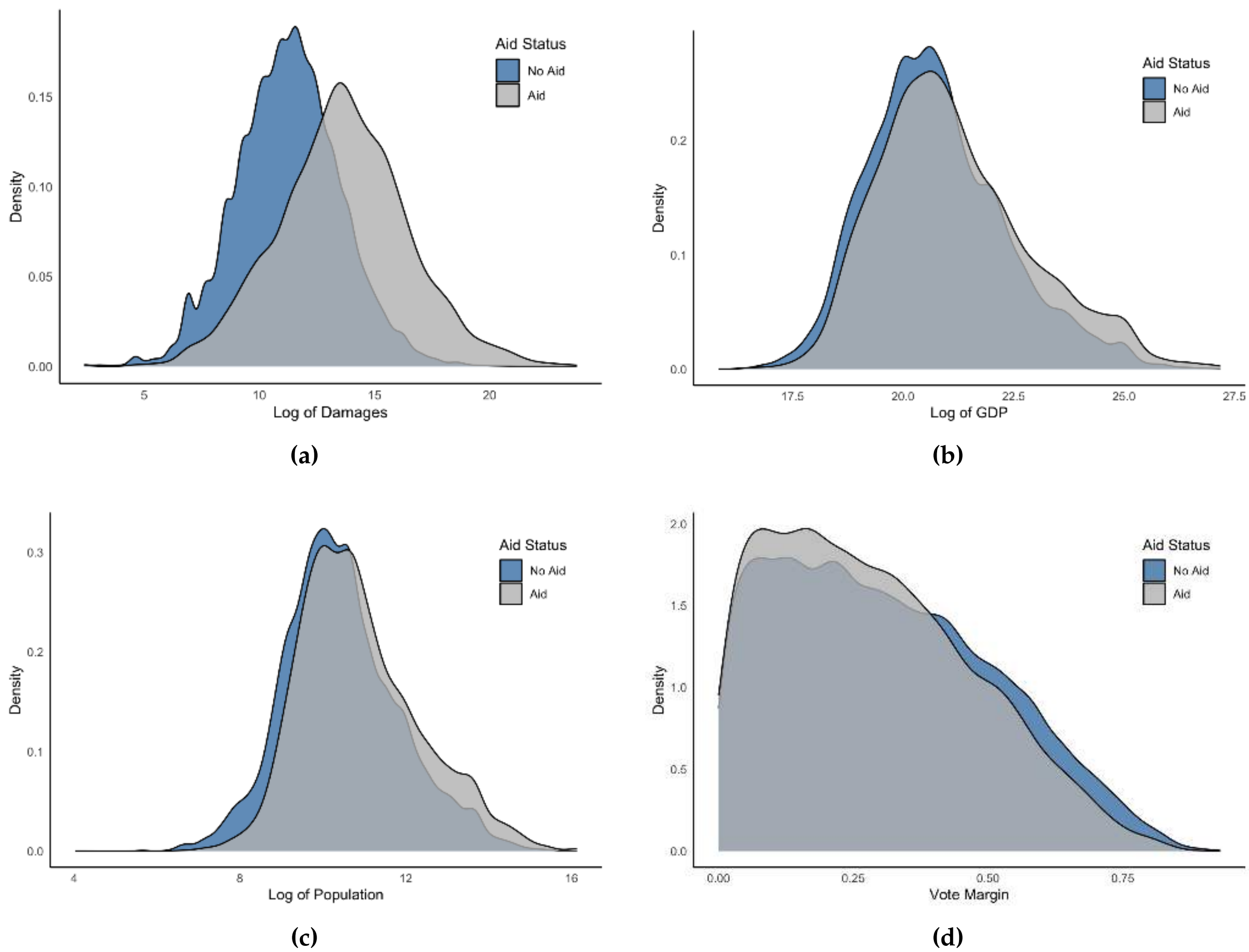

Figure 1: Distribution of county-specific factors by aid status. The gray distribution represents all the counties that were given aid, and the blue represents counties that were not given aid. Panel **(a)** plots the log-transformed total damages reported by SHELDUS. Panel **(b)** plots the distribution of log-transformed county GDP. Panel **(c)** plots the distribution of log-transformed county population. Panel **(d)** plots county-level presidential election vote margins.

aid (gray). This finding is consistent with the official damage-assessment framework carried out by FEMA before granting aid. Panels (b) and (c) show that counties with higher populations or GDP are more likely to receive higher aid. This may follow from panel (a) as counties with greater economic activity or more residents are more likely to suffer losses, triggering the need for federal assistance. Apart from these factors, FEMA notes on its website that part of the selection criteria depend on the citizenship status, household income and dependents, other insurance payouts, as well as occupancy and identity verification.

Panel (d) highlights distribution with respect to political competition proxied by vote margin.[9] From the data, we observe that the average county-level vote margins are lower for counties that receive aid. This correlation between political competition and aid receipt aligns with findings by Garrett and Sobel [2003] and Stramp [2013], who documented political influences on disaster aid at the state level. Their findings motivate our use of county-level vote margins as an instrument.

2.2 Related Literature

Most of studies that focus on the effects of disasters on economic outcomes find a negative effect in the short to medium-term, while a smaller strand of these studies find positive effects in the long run. For the positive effects, one potential channel is "build back better", in which destroyed capital is replaced with newer, more efficient technology, which can lead to neutral, or even positive, long-term outcomes (Hornbeck and Keniston [2017], Groen et al. [2020]). The difference in these outcomes can potentially be explained by factors such as adaptation (Neumayer et al. [2014]), institutional quality (Kahn [2005], Noy [2009]), and most importantly, the infusion of post-disaster aid and other transfers (Deryugina [2017], Roth Tran and Wilson [2025]).

Despite the massive scale of post-disaster aid, previous literature has largely focused on the general long-term effect of disasters themselves (Hsiang and Jina [2014]) rather than the specific mechanism of how aid drives local economic recovery. Most of these studies constructed comparable groups of counties that did and did not experience disasters to estimate the causal effect (Deryugina [2017]). The difference-in-differences approach works in their setting because the disaster itself is plausibly more exogenous than federal aid as federal aid is correlated with

[9] $\text{VotesMargin}_c = \frac{|\text{Votes}_{D,c} - \text{Votes}_{wR,c}|}{\text{Votes}_{D,c} + \text{Votes}_{R,c}}$ is the Vote Margin for county c where D refers to Democrat and R refers to Republican.

the unobserved severity of the damage and the undisclosed selection criteria.[10] Constructing comparable groups of counties that received varying levels of federal aid conditional on being hit by a disaster is more challenging. Furthermore, we cannot use the disaster itself as an instrument for aid since it could possibly affect economic recovery through other channels such as insurance payouts, migration, or changes in local investment.

A study closest to ours is Roth Tran and Wilson [2025], who analyze county-level data and estimate the impulse responses of the disaster that triggered FEMA aid on economic outcomes. They find that counties that receive federal aid post-disaster experience a long-run income boost. Their analysis considers counties that received FEMA aid post-disaster as a treatment group and counties without disasters as a control group. Their estimate can be interpreted as a combined effect of disaster and aid on economic outcomes. In comparison, we include all disaster-affected counties and assign to the treatment group only those that received federal aid. Thus, our estimate can be interpreted as the causal effect of federal aid alone on GDP recovery.

Another parallel stream of literature draws upon the political economy that underpins economic growth. Studies (Besley et al. [2010], Ma and McLaren [2018]) find that political competitiveness is positively associated with economic outcomes through the channel of strong political accountability. Competition forces politicians to appeal to swing voters, whose decisions are based on the parties' economic policy choices. This pressure incentivizes parties to shift away from special-interest policies and rent-seeking toward better governance and public goods provision. We argue that this accountability mechanism breaks down at the county-level in non-swing states. Under the winner-take-all Electoral College system, county-level political competition carries no electoral consequence when statewide outcomes are predetermined, eliminating the incentive for politicians to deliver better local economic performance. This breakdown in non-swing counties allows us to use political competition as an instrument for federal aid allocation. We argue that since political competition in non-swing states does not affect local economic outcomes directly, it can only affect economic outcomes through the channel of federal aid allocation. We test and confirm this claim empirically in Section 4.

A related strand of literature on aid distribution demonstrates that political factors play a role in the allocation of federal aid. Studies of federal disaster relief find that politically important districts receive a disproportionate share of government funds (Garrett and Sobel [2003], Stramp [2013]). This political influence operates through two primary channels. First, executive-level manipulation occurs as presidents can influence disaster declaration decisions or increase federal

[10] Areas along the Gulf Coast, the Atlantic Coast, and the Mississippi River are particularly prone to flooding. The West Coast and the central United States along the New Madrid fault line are at higher risk of earthquakes. Finally, Florida and the Carolinas, along with other counties near the Atlantic coast are often affected by hurricanes.

cost-share reimbursements to benefit electorally important swing states, particularly near an election. Second, members of key congressional oversight committees steer disproportionately larger funding allocations to their home states. Much of this literature operates at the state or national level, leaving less clarity around how these dynamics function at the local level. We extend this literature to the county-level, showing that political competition predicts aid allocation even within states, and providing the first causal estimates of how politically-driven aid affects local economic recovery.

3 Data

The primary source of disaster-related data for this paper comes from FEMA and SHELDUS. Spatial Hazard Events and Losses Database for the United States (SHELDUS) is a county-level dataset compiled by the Hazards and Vulnerability Research Institute at the University of South Carolina. It aggregates data from multiple federal sources to provide standardized estimates of hazard-related losses across the U.S. since 1960. It covers natural hazards such as thunderstorms, hurricanes, floods, wildfires, and tornadoes and contains information about the date of an event, affected location (county and state) and the direct losses caused by the event (property and crop losses, injuries, and fatalities). FEMA provides information on which natural disaster was approved or denied for government aid, as well as the total approved amount of aid.[11] Figure 2 presents a map of the total number of FEMA disaster declarations for each county during the study period, providing a visual representation of regional variation in disaster exposure.

To construct a comprehensive dataset of natural disasters in the United States containing losses and aid responses, we integrate information from both the FEMA and SHELDUS databases. FEMA offers detailed disaster-level data, while SHELDUS provides county-level information aggregated at the quarterly level. Due to differences in granularity between the two sources, our merged dataset does not retain unique disaster identifiers. Instead, we structure the data at the county-quarter level, enabling consistent alignment across these sources for analysis.[12]

Data on Small Business Administration (SBA) disaster loans are obtained from the SBA website. These loans typically compensate for approximately 11% of the total damages caused by a disaster.[13] In addition to low-interest loans, individuals residing in federally declared

[11] We use obligated amounts from FEMA's Individual Assistance (IA) and Public Assistance (PA) programs. See Section 2 for program details.
[12] Sources and Frequency of all variables can be found in Table A.9.
[13] Not all damages are approved for compensation by the SBA. Individuals must submit loan applications, which

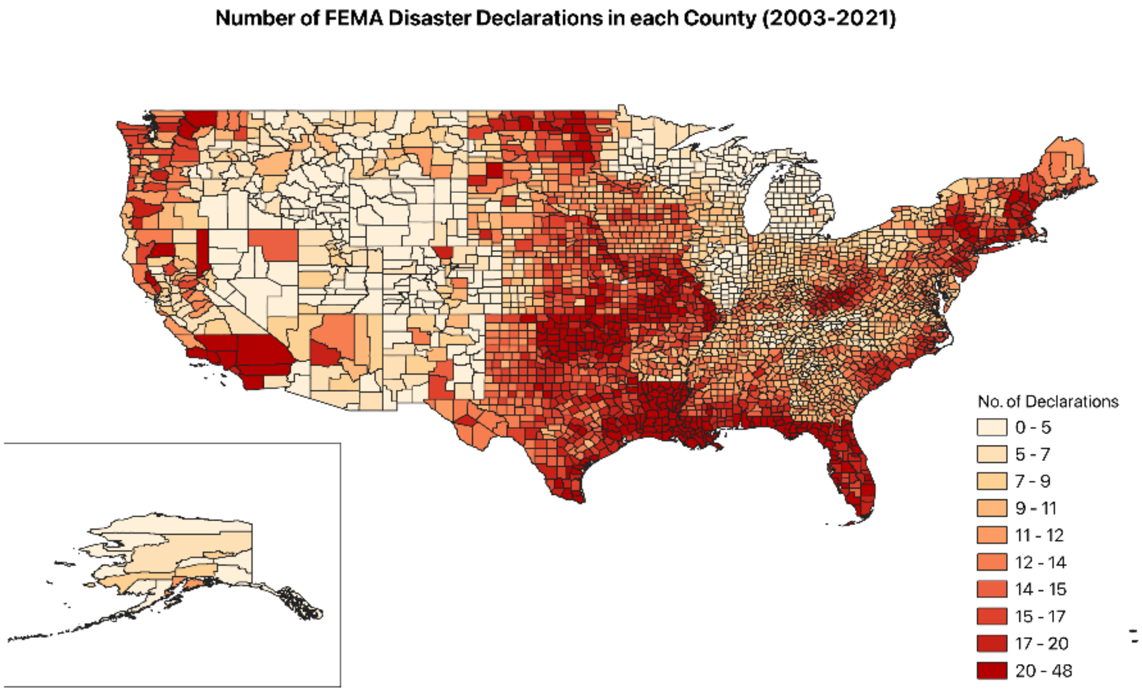

Figure 2: Spatial Distribution of FEMA Disaster Declarations across the United States

disaster areas are eligible for mortgage and housing assistance programs that are not available in non-declared areas. This variation in federal aid, conditional on disaster declaration status, enables comparison of economic outcomes between counties affected by the same disaster but receiving different levels of support. As SBA loan data is available only at the annual level, we distribute loans across quarters in proportion to each quarter's share of annual damages, and then merge this with our county-quarter-level disaster panel[14].

We obtain county-level annual outcome data from the Bureau of Economic Analysis (BEA), including measures for households, businesses, population, unemployment, and GDP. These outcomes are merged with disaster data from FEMA and SHELDUS at the county-quarter level to construct the primary panel used in our analysis. We structure the analysis at this quarterly frequency (repeating the annual BEA data for each quarter within a given year) because our

may reflect losses smaller than those recorded in SHELDUS. This discrepancy can arise if insurance covers part of the loss or if the individual opts out of taking on additional debt. On average, SBA loans amount to 49% of the applicant's verified loss, with a median of 44%.

[14] Results are robust to alternative allocation rules, including equal distribution across quarters within a year.

Table 1: Sample Sizes by Subpopulation

Subpopulation	Counties	Disasters	Observations	Mean Aid	Mean Damage
Full Panel	2,953	1,971	224,439	1.28	5.34
Non-Swing States	1,905	1,482	144,791	1.70	7.16
Swing States	1,048	489	79,648	0.64	2.54
Positive Damage	2,945	1,563	89,406	1.28	5.34
Positive Damage, Non-Swing	1,898	1,154	54,143	1.70	7.16
Positive Damage, Swing	1,047	409	35,263	0.64	2.54
Received Aid	2,803	1,675	19,118	8.02	29.89
Damage + Aid	2,635	1,386	14,250	8.02	29.89
Regression Sample	1,898	1,023	49,366	1.71	6.73

identification strategy relies on an instrumental variable defined by the distance in quarters from an election.

Additionally, we incorporate county-level presidential election vote shares from the MIT Election Data and Science Lab (MEDSL) and campaign spending data from the Federal Election Commission (FEC), which we aggregate to the quarterly level to align with our disaster dataset. For each county-election year, we calculate the vote margin as the absolute difference between the presidential Republican and Democratic vote shares, which captures the degree of political competition at the county level. For non-election years, we assign each county the vote margin from the most recent presidential election. Additionally, we classify states as "swing states" based on whether they changed partisan control of electoral votes at least once during the 2000–2020 period. Table 2 reports summary statistics for the key variables.

Our final dataset is a balanced panel at the county-quarter level spanning Q1 2003 to Q4 2021.[15] The full sample comprises 224,439 observations spanning 2,953 counties and 1,971 unique FEMA-declared disasters. Our specification includes controls for local economic conditions: total county-level Unemployment Insurance payments (government transfers to displaced workers), population, employment, and per-capita income. To account for disaster exposure and aid-seeking behavior, we control for Total Applications (FEMA aid requests) and Records (number of disaster event records in the county-quarter). We also include Election Spending to capture local political campaign activity. Table 1 details sample sizes across subpopulations. Our preferred IV specifications focus on non-swing states with positive recorded damages (49,366 observations across 1,898 counties).[16]

[15] The 2003 start date is determined by the availability of FEC election spending data.

[16] The regression sample excludes 4,777 observations for which the lead GDP variables cannot be computed due to the end-of-sample boundary.

Table 2: Summary Statistics for all Variables (Population: Full Panel)

Variable	Mean	SD	Min	Median	Max
Unemployment Insurance	31,844,651	246,696,083	1,000	3,808,000	31,503,026,000
Number of Jobs	60,519	209,846	53	12,518	6,582,546
Population	103,683	328,480	55	26,646	10,123,521
Damages	2,125,532	112,343,686	0.00	0.00	21,481,571,500
Income per Capita	37,470	12,598	11,522	35,229	318,297
Total Applications	91	3,020	0.00	0.00	615,608
Election Spending	35,318	1,794,456	0.00	0.00	535,041,907
Vote Margin	0.32	0.21	0.00	0.30	0.94
County GDP	4,762,193,329	20,844,836,245	7,468,000	783,264,000	647,355,553,000
Records	1	3	0.00	0.00	186

As disasters are rare but high-impact events, the median county-quarter experiences zero damages and zero aid applications. However, the mean damage is $2.13 million, indicating a highly right-skewed distribution. This motivates log-transforming damage and aid variables in the subsequent analysis. Our outcome and control variables also show substantial variation. The average county-quarter in our sample has a population of 104,000 and an annualized GDP of $5.1 billion. We also observe significant variation in presidential vote shares, with the average vote margin at 0.32 and a standard deviation of 0.21. This variation in vote margins is essential for our identification strategy.

Figure 3 plots total annual disaster damages, with 2017 recording the highest losses at approximately $99 billion, driven predominantly by hurricanes (95.2% of that year's total). Of this total, 13.2% of all disaster damages were covered by FEMA and SBA funding. Insurance coverage also falls well short; Dixon et al. [2020] find that local governments receive only 28% of repair costs on average, leaving a substantial unmet funding gap.

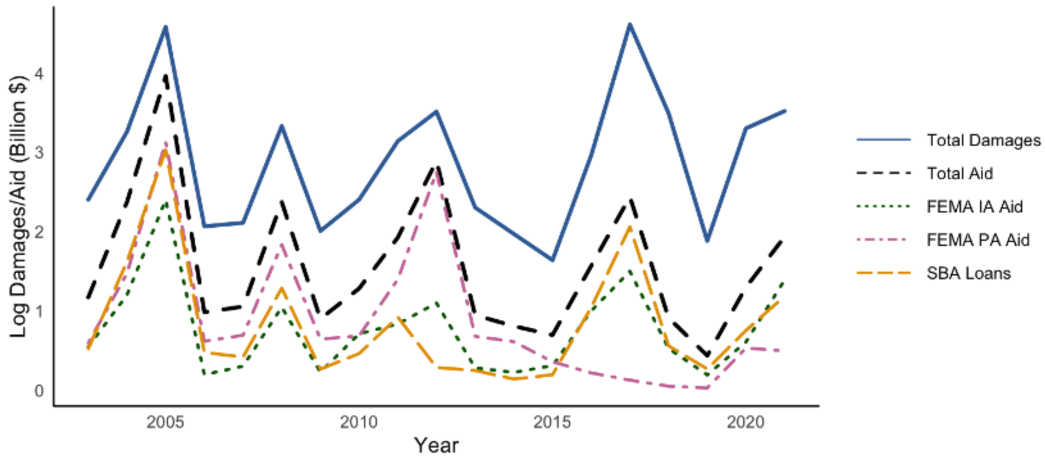

Figure 3: Graph of the total damages caused by natural disasters each year (blue) along with aggregate information such as total funding, FEMA aid, and loans given by the SBA.

4 Analysis and Results

4.1 Baseline Specification

We begin with the TWFE specification to identify the effect of federal aid on county-level GDP growth rate:

$$\Delta \log(\text{GDP})_{c,t+} = \beta \log(\text{Aid})_{c,t} + \gamma \mathbf{X}_{c,t} + \delta_c + \tau_t + \epsilon_{c,t} \tag{1}$$

where $\log(\text{Aid})_{c,t}$ is the log of federal aid received by county c in quarter t, X_{ct} represents time-varying county-level covariates and γ is the coefficient associated with X_{ct}. The coefficient τ_t represents quarter fixed effects, which we include to absorb macroeconomic shocks, nationwide trends, and seasonal fluctuations that affect all counties simultaneously. The coefficient δ_c represents county fixed effects to control for the time-invariant characteristics of a county, such as geographic vulnerability to disasters, long-run economic composition, and baseline institutional capacity.

The dependent variable $\Delta \log(\text{GDP})_{c,t+}$ is defined as $\log(\text{GDP}_{c,y+2}) - \log(\text{GDP}_{c,y+1})$, where y is the calendar year in which the disaster occurs[17]. Since county-level GDP from the BEA is

[17] An alternative would be to measure growth from the disaster year itself, i.e. $\log(\text{GDP}_{c,y+1}) - \log(\text{GDP}_{c,y})$. We avoid this construction because $\text{GDP}_{c,y}$ conflates pre- and post-disaster output within the same calendar year. For a disaster occurring late in year y (e.g. Q4), most of year y's GDP is generated before the shock, so the baseline is largely unaffected and the resulting growth rate captures both the initial damage and any subsequent recovery. In

available only at an annual frequency, this measure captures annual GDP growth in the year following the disaster year, regardless of which quarter within year y the disaster takes place. This construction ensures that the recovery window is identical for all observations, since it always spans calendar year $y+1$ to $y+2$ even though the elapsed time between the disaster quarter and the start of year $y+1$ naturally varies. Specifically, a disaster in Q1 of year y precedes the recovery window by three quarters, whereas a disaster in Q4 precedes by only one quarter. The coefficient of interest β therefore captures a weighted average of the aid effect across these different gap lengths. Let β_g denote the effect of federal aid on GDP recovery when the gap between the disaster and the start of the recovery window is g quarters. Then β can be written as $\beta = \sum_{g=0}^{3} w_g \beta_g$, where w_g reflects the share of disasters occurring in quarter $q = 4 - g$. Since disasters are more likely to occur in the second or third quarter of the calendar year, the weights are larger for $g = 1$ and $g = 2$.

The results for Eq. 1 are presented in panel (1) of Table 3 where the aid coefficient is statistically insignificant. This is consistent with a negative selection bias, since FEMA and the SBA allocate larger aid packages to counties that suffer more severe disasters, and these same counties would have experienced slower recovery even absent federal assistance. If aid genuinely accelerates recovery, this negative correlation between aid intensity and counterfactual growth biases OLS estimates toward zero (or negative), masking the true positive effect. The TWFE specification cannot resolve this endogeneity because county and time fixed effects do not absorb the within-county, time-varying severity of individual disaster events.

Panel (2) of Table 3 reports the specification with disaggregated aid into its three components: FEMA Individual Assistance (IA) grants, FEMA Public Assistance (PA) grants, and SBA disaster loans. The effect of aid on GDP growth is insignificant for FEMA IA and SBA. Notably, FEMA PA, which reimburses local governments for infrastructure repair, has a significant negative coefficient. One can argue that the negative bias through selection criteria overcompensates for the positive effect of aid. But since FEMA PA's correlation with damages breaks down post 2016 (Figure 3), it follows a different path compared to FEMA IA and SBA. Thus, the negative coefficient for FEMA PA may be driven by this post-2016 deviation rather than a genuine negative effect. Standard errors are clustered at the county level in both specifications.

contrast, for a disaster early in year y (e.g. Q1), the damage is already embedded in $\text{GDP}_{c,y}$, so the same growth measure primarily reflects recovery. Using $\text{GDP}_{c,y+1}$ as the base avoids this contamination: by year $y+1$, the initial shock has been absorbed regardless of disaster timing within year y, and the dependent variable isolates the recovery effect that we seek to attribute to federal aid.

Table 3: Regression of GDP Growth on Federal Assistance

Dependent Variable:	$\Delta \log(\text{GDP})_{c,t+}$	
	Aggregated Aid	Disaggregated Aid
Model:	(1)	(2)
Variables		
Log All Aid	-0.0001	
	(0.0001)	
Log IA Aid		0.0002
		(0.0003)
Log PA Aid		-0.0004***
		(0.0001)
Log SBA Loans		1.4×10^{-5}
		(0.0001)
Log Unemployment Insurance	-0.0179***	-0.0180***
	(0.0019)	(0.0019)
Log Number of Jobs	-0.0340***	-0.0340***
	(0.0130)	(0.0130)
Log Population	0.0073	0.0071
	(0.0175)	(0.0174)
Log Damages	0.0002	0.0002
	(0.0002)	(0.0002)
Log Income per Capita	-0.1883***	-0.1882***
	(0.0133)	(0.0133)
Log Applications	0.0003	0.0003
	(0.0003)	(0.0006)
Log Records	0.0002	0.0002
	(0.0006)	(0.0006)
Log Election Spending	-0.0002*	-0.0002*
	(0.0001)	(0.0001)
Fixed-effects		
County	Yes	Yes
Quarter	Yes	Yes
Fit statistics		
Observations	81,293	81,293
R^2	0.15227	0.15242
Within R^2	0.02124	0.02141

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.2 Instrumental Variable

To deal with the endogeneity concern regarding selection bias, we turn to an instrumental variable approach to isolate the causal effect of federal disaster aid on economic recovery. Our identification strategy uses the variation in political competitiveness (vote margin) between counties as an instrument for the amount of federal disaster aid received. Ideally, we want to assign the disaster affected counties into treatment (with aid) and control group (without aid) where the assignment criterion is related to the political competition (relevance condition) but not related in any way to counties' GDP, making the assignment as good as random (exogeneity condition).

The relevance condition is supported by economic theory. Several studies suggest that politically competitive areas are more likely to receive a disproportionate share of government funds (Garrett and Sobel [2003], Stramp [2013]), and we believe that the same should hold true for federal disaster assistance at the county level. Swing counties may receive preferential treatment in federal aid allocation relative to non-swing counties.

However, the exogeneity condition is difficult to defend directly, as a substantial body of literature documents that political competition is associated with economic welfare. Politicians have an incentive to choose welfare-maximizing policies over rent-seeking when electoral outcomes are uncertain (Besley et al. [2010]). To test for the violation of exogeneity condition, we estimate the following TWFE model:

$$\Delta \log(\text{GDP})_{c,t} = \lambda \text{Margin}_{c,t-} + \gamma \mathbf{X}_{c,t} + \delta_c + \tau_t + \epsilon_{c,t} \tag{2}$$

where $\text{Margin}_{c,t-}$ represents the vote margin of the last presidential election for county c at time t, $\Delta \log(\text{GDP})_{c,t}$ is the annual GDP growth rate for the current year and λ is the coefficient capturing effect of $\text{Margin}_{c,t}$ on GDP recovery. The results of this estimation are presented in panel (1) of Table 4. We observe significant negative effects of the Vote Margin on GDP growth rate suggesting that political competition is positively associated with GDP growth rate. We also estimate this model on two subsamples: First, county-quarters in which a disaster occurred (panel (2)) and second, county-quarters with no disasters (panel (3)). The effect is negative and significant in both panels. Panel (3) isolates the direct association between political competition and GDP growth by restricting to periods where no aid was disbursed, thus acts as the most appropriate test for the exogeneity condition. The negative and significant effect serves as evidence for the violation of the exogeneity condition.

Table 4: Regression of GDP Growth on Vote Margin

Dependent Variable:	$\Delta \log(\text{GDP})_{c,t}$		
Panel:	All Data	Disasters	No Disasters
	(1)	(2)	(3)
Margin	-0.0328***	-0.0521***	-0.0208**
	(0.0065)	(0.0066)	(0.0084)
Log All Aid	6.03×10^{-5}	-1.15×10^{-6}	0.0001
	(9.7×10^{-5})	(0.0001)	(0.0002)
Log Unemployment Insurance	-0.0186***	-0.0173***	-0.0191***
	(0.0017)	(0.0018)	(0.0021)
Log Number of Jobs	-0.0929***	-0.0986***	-0.0931***
	(0.0141)	(0.0132)	(0.0168)
Log Population	0.0423**	0.0446***	0.0427**
	(0.0166)	(0.0170)	(0.0204)
Log Damages	-7.76×10^{-5}	0.0002	
	(8.22×10^{-5})	(0.0002)	
Log Income per Capita	-0.1543***	-0.1556***	-0.1568***
	(0.0110)	(0.0124)	(0.0128)
Log Records	0.0006	0.0002	0.0051***
	(0.0006)	(0.0006)	(0.0019)
Log Election Spending	0.0001	-0.0002	0.0003**
	(0.0001)	(0.0001)	(0.0001)
Log Applications	6.43×10^{-5}	-0.0002	0.0005
	(0.0003)	(0.0003)	(0.0006)
Fixed-effects			
County	Yes	Yes	Yes
Quarter	Yes	Yes	Yes
Fit statistics			
Observations	200,260	81,287	118,947
R^2	0.09185	0.15083	0.09041
Within R^2	0.02176	0.02229	0.02183

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

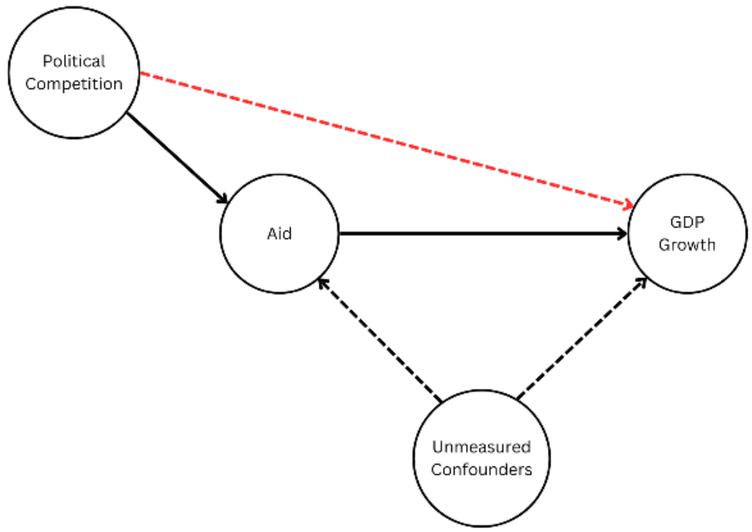

Figure 4: Exogeneity of IV

4.3 Exogeneity Condition: Political Competition and GDP Growth Rate

To overcome the concern of correlation between political competition and GDP growth rate, we limit our analysis to the subset of counties located in non-swing states. A state is defined as a swing state if the winning party in the state changed at least once during our study period. As a robustness check, we also use a cutoff criterion where we define a state as swing if the difference in vote shares of the two major parties is less than 10%, 15%, or 20%. In non-swing states, county-level political competition does not influence presidential election outcomes, as electoral votes are allocated on a winner-take-all basis and statewide vote shares determine the outcome. Consequently, local politicians have no incentive to strategically improve local economic conditions in response to electoral competitiveness. This ensures that, within non-swing states, political competition affects economic outcomes only through the aid channel. We illustrate this mechanism in Figure 4, where the direct path from political competition to GDP growth can be eliminated if we restrict our data to non-swing states. The interpretation of our instrument is as follows: political competition among counties in non-swing states affects GDP growth only through the federal aid channel.

We examine the violation of exogeneity condition in our new setting by checking whether county-level political competition directly influences GDP growth in periods when disaster aid cannot operate as a channel. We regress GDP growth on county vote margins using only the subset of county-quarter observations with no disasters, ensuring that no federal aid was disbursed in these quarters. We estimate Equation 2 separately for swing and non-swing states, allowing us to compare whether political competition significantly affects GDP growth in environments where electoral incentives differ. The results of this estimation are presented in Table 5.

Across all definitions of swing states, we find that the coefficient on vote margin is statistically insignificant for non-swing states, but consistently negative and significant for swing states. This pattern aligns with our hypothesis that incentives for political actors to influence local economic conditions through improved governance or targeted policy efforts are present only where county-level competition is relevant, which is only in swing states. In non-swing states, where statewide outcomes are effectively predetermined, county-level political competition does not translate into differential economic performance.

4.4 Relevance Condition: Political Competition and Federal Aid

For the first stage of our 2SLS estimation, we regress log of Federal Aid on the county-level vote margin given as

$$\log(\text{Aid})_{c,t} = \alpha \text{Margin}_{c,t} + \gamma \mathbf{X}_{c,t} + \delta_c + \tau_t + \epsilon_{c,t} \tag{3}$$

where, α is the estimated impact of political competition on the allocation of disaster aid. The results from Equation 3 are presented in Table 6[18]. We find the coefficient to be negative and significant, which represents a strong positive association between political competition and aid distribution. Counties with a lower vote margin in the previous election get a higher aid allocation compared to counties with a higher vote margin. Since our IV is exogenous only in non-swing states, columns (2) and (3) present first stage results for Equation 3 when data is restricted to only swing and non-swing states respectively.

We observe that results persist for the sample of non-swing states where the effect of political competition on disaster aid is negative and statistically significant with an F statistic of 22.9. Counties with tighter vote margins receive substantially more federal assistance following a disaster. Surprisingly, the relationship is statistically insignificant within swing states with a low F statistic of 0.43. This points toward the existence of heterogeneity in how political incentives

[18] To evaluate the political bias at a disaggregated level, we also regress margin on individual components of aid (IA, PA, and SBA). The results for this regression are presented in table A.10. We find that political bias in Aid is the strongest for SBA and the weakest for IA in non-swing states. We also find that higher political competition has a negative effect on SBA aid in swing states.

Table 5: Estimated impact of political competition on GDP growth for the subset of data with no disasters.

Dependent Variable:	$\Delta \log(\text{GDP})_{c,t}$	
	Swing States	Non-Swing States
Model:	(1)	(2)
Panel A: Swing State Historical Classification		
Margin	-0.0443***	-0.0099
	(0.0093)	(0.0115)
Observations	38,882	80,065
Median No. of States	15	33
Panel B: Swing State Cutoff Classification (cutoff = 0.10)		
Margin	-0.0287**	-0.0194
	(0.0113)	(0.0130)
Observations	46,535	72,317
Avg. No. of States	15	32
Panel C: Swing State Cutoff Classification (cutoff = 0.15)		
Margin	-0.0258*	-0.0132
	(0.0148)	(0.0140)
Observations	63,812	55,095
Avg. No. of States	23	24
Panel D: Swing State Cutoff Classification (cutoff = 0.20)		
Margin	-0.0257**	0.0131
	(0.0101)	(0.0202)
Observations	84,145	34,753
Avg. No. of States	31	17
Fixed-effects		
Quarter	Yes	Yes
County	Yes	Yes

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Regression of Disaster Aid on Political Competition

Dependent Variable:	log (Aid)$_{c,t}$		
	All Data	Swing	Non-Swing
Model:	(1)	(2)	(3)
Variables			
Margin	-0.6289***	-0.1448	-0.8758***
	(0.1929)	(0.3231)	(0.2457)
Log Unemployment Insurance	-0.2051***	-0.0305	-0.3792***
	(0.0441)	(0.0693)	(0.0659)
Log Number of Jobs	-0.1186	-1.074**	0.3146
	(0.2744)	(0.4513)	(0.3402)
Log Population	-0.9675***	-0.9552	-0.6483
	(0.3564)	(0.6112)	(0.4287)
Log Damages	0.1515***	0.1368***	0.1628***
	(0.0072)	(0.0108)	(0.0096)
Log Income per Capita	0.6609***	2.235***	-0.0402
	(0.2366)	(0.4470)	(0.2740)
Log Applications	2.247***	2.169***	2.283***
	(0.0154)	(0.0233)	(0.0199)
Log Records	-0.0114	0.1722***	-0.1425***
	(0.0281)	(0.0421)	(0.0368)
Log Election Spending	-0.0071	-0.0101	-0.0033
	(0.0056)	(0.0075)	(0.0082)
Fixed-effects			
County	Yes	Yes	Yes
Quarter	Yes	Yes	Yes
Fit statistics			
F-test (1st stage)	20.117	0.43293	22.948
Observations	81,287	31,970	49,317

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

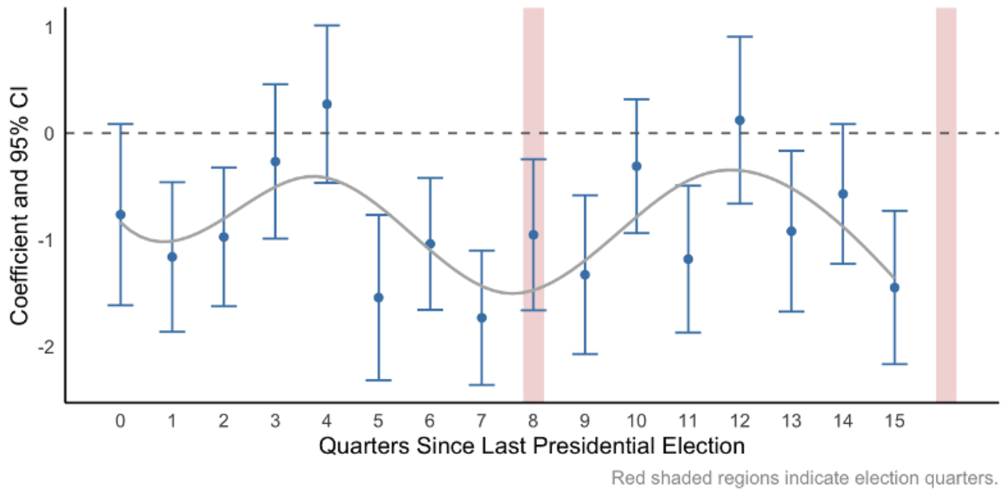

Figure 5: Coefficients for Equation 4. Data restricted to non-swing states. Horizontal axis represents number of quarters until next elections. The red vertical line at the 8th quarter represents state legislative elections that occur biannually and the red vertical line at 16th quarter represents presidential elections that occur once in 4 years. The vertical axis represents the coefficient values along with 95% confidence interval.

shape the aid distribution. One plausible interpretation is that non-swing states strategically channel disproportionate aid toward their swing counties in an effort to influence future electoral outcomes. Swing states, by contrast, may pursue a more uniform allocation strategy given that the entire state is electorally competitive.

To further investigate, we analyze the political bias in aid allocation relative to the timing of disaster with respect to the next presidential election, allowing political incentives to vary systematically over the electoral cycle. We expect the effect to be stronger the closer the disaster timing is to the election. We modify the first-stage equation and restrict the data to the subset of non-swing states, consistent with the exogeneity conditions established earlier.

$$\log(\text{Aid})_{c,t} = \sum_{q=0}^{15} \alpha_q (\text{Margin}_{c,t} \times \mathbb{I}_t(\text{PostElection} = q)) + \gamma \mathbf{x}_{c,t} + \delta_c + \tau_t + \epsilon_{c,t} \tag{4}$$

Here, the interaction between county-level vote margin and indicator variables for the number of quarters elapsed since the last presidential election captures how the effect of political competition on aid evolves over the electoral cycle, allowing us to detect heterogeneous effects of political competition on disaster aid allocation. We plot the coefficients from the estimation of Equation 4 in Figure 5.

We observe that there is a cyclical pattern to the effect itself. In the quarters immediately preceding the election, the tendency to allocate disaster aid to politically competitive counties increases sharply. The results are consistent with the idea that policy makers try to take advantage of voter recency bias. Aid that is distributed shortly before an election is more visible and therefore more likely to influence voter evaluations. The effect is weakest in the 4^{th} and 12^{th} quarters, which is the farthest one can get from any elections. In contrast, immediately after an election, when both federal and state-level electoral incentives are at their lowest, the effect starts to fade away in the following quarters.

4.5 Second Stage: Federal Aid and GDP Recovery

We now estimate the second-stage regression of GDP growth on the log of federal disaster aid, specified as,

$$\Delta \log(\text{GDP})_{c,t+} = \beta \widehat{\log \text{Aid}}_{c,t} + \gamma \mathbf{X}_{c,t} + \delta_c + \tau_t + \epsilon_{c,t} \tag{5}$$

where, $\widehat{\log(\text{Aid})}_{c,t}$ denotes the fitted values of the disaster aid obtained from the first-stage estimation. The results, reported in Table 7, indicate a positive and statistically significant effect of federal disaster aid on one-year-ahead GDP growth. The estimated coefficient of 0.0527 implies that a 1% increase in disaster aid leads to a 5.27 basis-point increase in county-level GDP growth following the receipt of aid.

We also examine potential long-term effects of federal disaster aid on economic performance by replacing the dependent variable with two-year, three-year, and four-year-ahead GDP growth rates. The results are presented in Figure 6 where we plot the coefficients of each of these regressions along with their 95% confidence intervals. We find that the magnitude and significance of the estimate decline sharply from year two onward. This pattern indicates that while disaster aid stimulates short-run economic recovery, we find no evidence of its persistence from the second year onward.

4.6 Fiscal Multiplier of Disaster Aid

Using our estimates of causal effect, we calculate the fiscal multiplier of disaster aid to assess the return per dollar of federal spending at the county level. Based on disaster affected counties in non-swing states, our coefficient of 0.0527 translates into a fiscal multiplier of approximately 1.79

Table 7: Second Stage IV Regression

Dependent Variable:	$\Delta\log(\text{GDP})_{c,t+}$
Model:	(1)
Variables	
$\widehat{\text{Log Aid}}$	0.0527***
	(0.0183)
Log Unemployment Insurance	0.0008
	(0.0079)
Log Number of Jobs	-0.1311***
	(0.0243)
Log Population	0.1024***
	(0.0309)
Log Damages	-0.0084***
	(0.0030)
Log Income per Capita	-0.1610***
	(0.0217)
Log Applications	-0.1210***
	(0.0420)
Log Records	0.0094***
	(0.0033)
Log Election Spending	-3.81×10^{-5}
	(0.0005)
County FE	Yes
Quarter FE	Yes
Fit statistics	
Observations	49,317
R^2	0.14500
Within R^2	0.02226

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

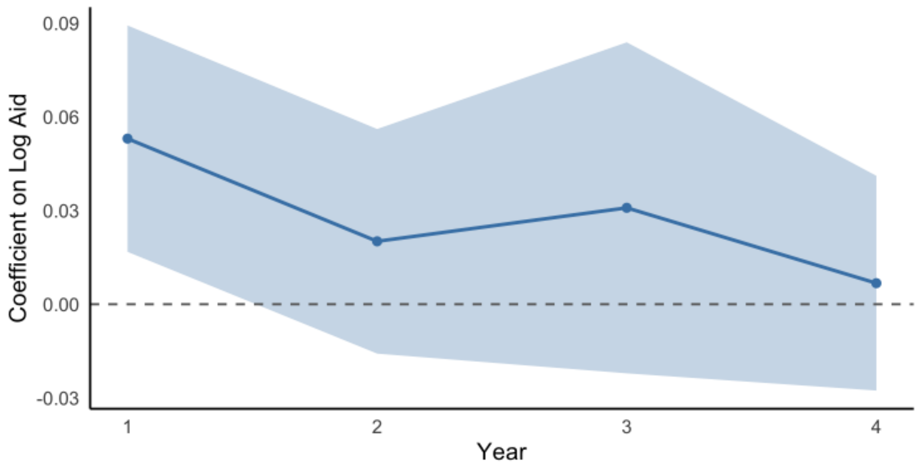

Figure 6: Long term impact of Disaster Aid on GDP growth rate

when restricting to counties with positive recorded damages (see Table 8).[19] Since our estimate is based on the counties with non-zero aid, we re-estimate the multiplier for the subsample of counties with both positive damage and positive aid in non-swing states and obtain a fiscal multiplier of approximately 1.98 (see Table 8).

Table 8: Fiscal Multipliers of Disaster Aid

Sample	Fiscal Multiplier
Positive Damage and Positive Aid	1.9842
Positive Damage	1.7874

Notes: The table reports estimated fiscal multipliers of disaster aid. Positive damage counties include only counties directly affected by a natural disaster. Positive aid counties include counties that received aid after a disaster. All counties include the full sample of counties in non-swing states.

To contextualize our estimates, we compare the recovery effect of federal aid with disaster-induced economic losses documented in the literature. At the U.S. county level, Strobl [2011] estimates that hurricanes reduce annual economic growth by 0.45 percentage points in affected

[19] The fiscal multiplier measures how many dollars of GDP are generated per dollar of federal disaster aid. We compute the multiplier as

$$\text{Multiplier} = \frac{\tilde{Y}\,(\beta/100)}{\tilde{A}},$$

where $\tilde{Y}$ denotes the median county GDP, $\tilde{A}$ denotes the median amount of disaster aid received conditional on positive aid, and β is the estimated coefficient from the specification measuring the percent change in GDP growth associated with a 1% increase in disaster aid. For example, with $\beta = 0.053$, $\tilde{A} = \$236,191$, and $\tilde{Y} \approx \$787$ million, we back out a multiplier of 1.77. This means that a 1% increase in aid ($2,362) generates a 0.053 percentage point increase in GDP growth, yielding a GDP increase of approximately $4,180.

coastal counties, though these effects net out at the state and national levels. Belasen and Polachek [2008] document employment declines of 1.5–5% in directly affected Florida counties depending on hurricane intensity. Boustan et al. [2020] find that severe disasters increase out-migration by 1.5 percentage points and lower housing prices by 2.5–5%, consistent with falling local productivity and labor demand. Over longer horizons, Deryugina [2017] estimates that stronger hurricanes cause per capita earnings losses exceeding $4,300 in net present value over the following decade, with employment effects persisting up to ten years. Jerch et al. [2023] document that hurricanes similarly reduce local government tax revenues, expenditures, and debt financing capacity over a comparable horizon. At the cross-country level, Noy [2009] finds that disasters reduce output growth by approximately 9 percentage points in developing countries, with substantially smaller effects in developed economies where stronger institutions and higher incomes buffer the initial shock.

These estimates generally capture the *net* effect of disasters—combining the initial shock with subsequent recovery channels, including federal aid. Our fiscal multiplier implies that every dollar of federal disaster aid generates approximately $1.80–$2.00 in local GDP within the following year. Since federal aid in our sample covers approximately 23.4% of recorded damages, aid-driven GDP recovery compensates for a meaningful share of short-run losses. The multiplier exceeding unity implies that the GDP return on federal disaster spending is positive. However, since the effect dissipates beyond one year (Figure 6), federal aid alone cannot address the persistent medium- and long-run consequences documented by Deryugina [2017] and Hsiang and Jina [2014]. The longer-run income recovery found by Roth Tran and Wilson [2025], who document that disasters triggering federal aid raise personal income per capita over an eight-year horizon, may instead reflect insurance payouts, private investment, and the replacement of destroyed capital with more productive technology [Hornbeck and Keniston, 2017].

5 Conclusion

This paper provides new causal evidence on the role of federal disaster assistance in local economic recovery. Using a comprehensive county-level panel of U.S. disasters from 2003 to 2021, we study how FEMA grants and SBA disaster loans affect post-disaster GDP growth. We instrument for aid using county-level political competition, exploiting the fact that this relationship satisfies the exclusion restriction only in non-swing states under the winner-take-all Electoral College. Conditioning on counties affected by disasters, we estimate the causal effect of federal aid on county-level GDP recovery. Our IV estimates imply that a 1% increase in disaster aid leads to a 5.3 basis-point increase in GDP growth in the year following the disaster, with effects dissipating in subsequent years. The multiplier exceeding unity implies that the GDP return on federal disaster spending is positive. However, since the effect dissipates beyond one year (Figure 6), federal aid alone cannot address the persistent medium- and long-run consequences documented by Deryugina [2017] and Hsiang and Jina [2014]. The longer-run income recovery found by Roth Tran and Wilson [2025]—who document that disasters triggering federal aid raise personal income per capita over an eight-year horizon—may instead reflect insurance payouts, private investment, and the replacement of destroyed capital with more productive technology [Hornbeck and Keniston, 2017].

From a research perspective, our heterogeneous findings of political competition on federal aid distribution between swing and non swing states can be a topic of future research. Researchers can also use the identification strategy to estimate effect of federal aid on other important macroeconomic variables. From a policy perspective, our results suggest that federal disaster assistance can play a meaningful role in accelerating short-run economic recovery but that its effects may not translate into long-term growth. This highlights the importance of designing aid programs that not only provide immediate relief but also support sustained economic rebuilding. Against the backdrop of ongoing structural reforms to federal disaster assistance, this paper provides evidence on the causal effect of FEMA aid on county-level recovery outcomes, with implications for the design and targeting of disaster relief policy.

References

Ann M. Beauchesne. *A Governor's Guide to Emergency Management: Volume One, Natural Disasters*. National Governors' Association, Washington, DC, 2001.

Ariel R Belasen and Solomon W Polachek. How hurricanes affect wages and employment in local labor markets. *American Economic Review*, 98(2):49–53, 2008. doi: 10.1257/aer.98.2.49.

Timothy Besley, Torsten Persson, and Daniel M. Sturm. Political competition, policy and growth: Theory and evidence from the US. *The Review of Economic Studies*, 77(4):1329–1352, 2010. doi: 10.1111/j.1467-937X.2009.00586.x.

Stephen B. Billings, Emily Gallagher, and Lowell Ricketts. Let the Rich Be Flooded: The Distribution of Financial Aid and Distress after Hurricane Harvey, May 2019. URL https://papers.ssrn.com/abstract=3396611.

Leah Platt Boustan, Matthew E Kahn, Paul W Rhode, and Maria Lucia Yanguas. The effect of natural disasters on economic activity in US counties: A century of data. *Journal of Urban Economics*, 118:103257, 2020. doi: 10.1016/j.jue.2020.103257.

Meri Davlasheridze and Pinar C. Geylani. Small business vulnerability to floods and the effects of disaster loans. *Small Business Economics*, 49(4):865–885, 2017. doi: 10.1007/s11187-017-9859-5.

Tatyana Deryugina. The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance. *American Economic Journal: Economic Policy*, 9(3):168–198, August 2017. ISSN 1945-7731. doi: 10.1257/pol.20140296. URL https://www.aeaweb.org/articles?id=10.1257/pol.20140296.

Lloyd Dixon, Jason Thomas Barnosky, and Noreen Clancy. Insuring Public Buildings, Contents, Vehicles, and Equipment Against Disasters: Current Practices of State and Local Government and Options for Closing the Insurance Gap. Technical report, RAND Corporation, October 2020. URL https://www.rand.org/pubs/research_reports/RRA332-1.html.

Thomas A. Garrett and Russell S. Sobel. The Political Economy of FEMA Disaster Payments. *Economic Inquiry*, 41(3):496–509, 2003. ISSN 1465-7295. doi: 10.1093/ei/cbg023. URL https://onlinelibrary.wiley.com/doi/abs/10.1093/ei/cbg023.

Jeffrey A Groen, Mark J Kutzbach, and Anne E Polivka. Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *Journal of Labor Economics*, 38(3):653–685, 2020. doi: 10.1086/706055.

Richard Hornbeck and Daniel Keniston. Creative destruction: Barriers to urban growth and the Great Boston Fire of 1872. *American Economic Review*, 107(6):1365–1398, 2017. doi: 10.1257/aer.20141707.

Solomon M Hsiang and Amir S Jina. The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Technical report, National Bureau of Economic Research, 2014. URL https://www.nber.org/papers/w20352.

Rhiannon Jerch, Matthew E Kahn, and Gary C Lin. Local public finance dynamics and hurricane shocks. *Journal of Urban Economics*, 134:103516, 2023. doi: 10.1016/j.jue.2022.103516.

Matthew E Kahn. The death toll from natural disasters: The role of income, geography, and institutions. *Review of Economics and Statistics*, 87(2):271–284, 2005. doi: 10.1162/0034653053970339.

Carolyn Kousky, Erwann O. Michel-Kerjan, and Paul A. Raschky. Does federal disaster assistance crowd out flood insurance? *Journal of Environmental Economics and Management*, 87:150–164, 2018. doi: 10.1016/j.jeem.2017.05.010.

Xiangjun Ma and John McLaren. A swing-state theorem, with evidence. Technical report, National Bureau of Economic Research, 2018. URL https://www.nber.org/papers/w24425.

Eric Neumayer, Thomas Plümper, and Fabian Barthel. The political economy of natural disaster damage. *Global Environmental Change*, 24:8–19, 2014. doi: 10.1016/j.gloenvcha.2013.10.012.

Ilan Noy. The macroeconomic consequences of disasters. *Journal of Development Economics*, 88(2): 221–231, 2009. doi: 10.1016/j.jdeveco.2008.02.005.

Brigitte Roth Tran and Daniel J Wilson. The local economic impact of natural disasters. *Journal of the Association of Environmental and Resource Economists*, 12(6):1667–1704, 2025. doi: 10.1086/726036.

Nicholas R Stramp. The contemporary presidency: Presidents profiting from disasters: Evidence of presidential distributive politics. *Presidential Studies Quarterly*, 43(4):839–865, 2013. doi: 10.1111/psq.12071.

Eric Strobl. The economic growth impact of hurricanes: Evidence from US coastal counties. *Review of Economics and Statistics*, 93(2):575–589, 2011. doi: 10.1162/REST_a_00082.

Maria Watson, Yu Xiao, Jennifer Helgeson, and Maria Dillard. The role of SBA loans in small business survival after disaster events. *Journal of Planning Education and Research*, 2021. doi: 10.1177/0739456X211028291.

Appendix

A.1 Variable descriptions

Table A.9: Variable descriptions

Variable	Frequency	Source
GDP	Annual	BEA
Population	Annual	BEA
Unemployment	Annual	BEA
SBA Loans	Annual	SBA
FEMA Aid	Monthly	OpenFEMA
Damages	Quarterly	SHELDUS
Election Spending	Quarterly	FEC
Election Vote Shares	Quadrennial	MEDSL

A.2 Additional figures

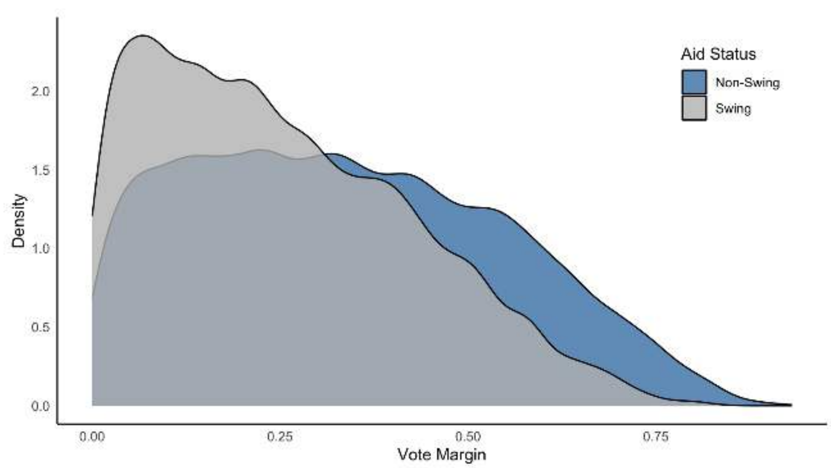

Figure A.7: Distribution of county-level vote margin by swing and non-swing states.

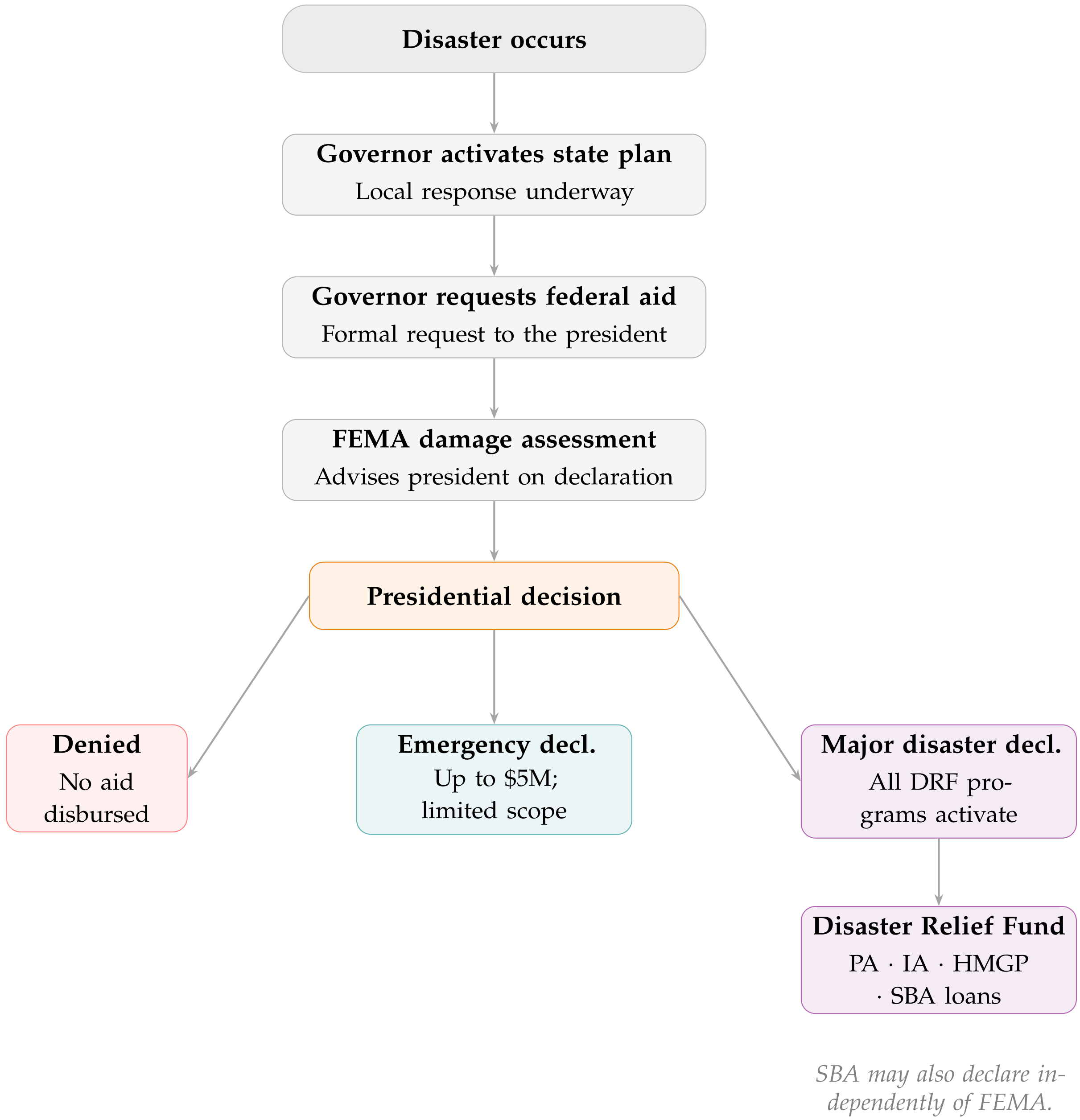

Figure A.8: Federal disaster aid declaration process. The Stafford Act (1988) governs the full process. Only major disaster declarations activate the full suite of FEMA and SBA programs studied in this paper.

A.3 Additional First-stage results

Table A.10: First-Stage IV Results (All Permutations)

	First Stage		
Dependent Variable	Margin	F-statistic	Observations
Individual Assistance			
All States	−0.0344	0.28	81,287
	(0.0669)		
Swing States	0.1870	4.14	31,970
	(0.1039)		
Non-Swing States	−0.1945*	4.81	49,317
	(0.0876)		
Public Assistance			
All States	−0.4709***	13.80	81,287
	(0.1423)		
Swing States	−0.2043	1.24	31,970
	(0.2038)		
Non-Swing States	−0.4814*	7.89	49,317
	(0.1920)		
SBA			
All States	−0.0929	0.49	81,287
	(0.1886)		
Swing States	0.6444*	8.97	31,970
	(0.3166)		
Non-Swing States	−0.5929*	12.24	49,317
	(0.2380)		

Notes: This table reports first-stage IV estimates of disaster aid on political competition (Margin). Standard errors clustered at the county level are shown in parentheses. All specifications include county and year-quarter fixed effects. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.