Do Politics Shape Economic Recovery through Disaster Aid? County-Level Evidence from U.S.

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Abstract

We estimate the causal effect of FEMA aid and SBA loans (federal aid) on economic recovery post disaster in the United States from 2003-2021. For the identification, we use a novel instrument based on the political competition within county and it's effect on the volume of federal aid distribution, especially when disaster occurs closer to the election. Due to the winner-takes-all nature of the US election, we argue that in non-swing states, politicians in the swing counties have no incentive to perform any better, and thus political competitiveness affects GDP only through federal aid. We find that a 1% increase in disaster aid results in a 0.03% increase in local GDP for the next year. With respect to the literature on political competition, we found evidence that political competition within a county is positively associated with 1) higher volume of disaster aid in non-swing states and 2) higher GDP growth rate in swing states.

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

1 Introduction

Natural disasters cause ~12 billion dollars worth of 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 and the Small Business Administration (SBA) offers low-interest rate loans (together we will refer to them as federal aid). This federal aid, on average, amounts to 23.4% of the recorded yearly damages, which is approximately \$4 billions[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.

There is a great deal of literature that focuses on the effects of disasters on economic outcomes. Most of these studies found a negative effect in the short to medium term (e.g.Kahn [2005], Belasen and Polachek [2008], Noy [2009], Strobl [2011], Hsiang and Jina [2014], Lazzaroni and van Bergeijk [2014], Klomp and Valckx [2014], Neumayer et al. [2014], Deryugina [2017], Deryugina et al. [2018], Botzen et al. [2019], Boustan et al. [2020], Jerch et al. [2023] etc.), while few studies found positive effects in the long run (e.g. Hornbeck and Keniston [2017], Groen et al. [2020], Roth Tran and Wilson [2025]). For the positive effects, potential economic channels could be "build back better" (Hornbeck and Keniston [2017]) or federal aid (including non-disaster government transfers as shown by Deryugina [2017]). Roth Tran and Wilson [2025] investigated the joint effect of the disaster and federal aid on future economic outcomes. However, none of the studies focus on estimating the direct effect of federal aid on economic recovery.

This paper investigates how FEMA grants (Individual Assistance (IA) grants in particular) and low-interest rate loans by the SBA affect GDP recovery at the county level post disaster. To our knowledge, this is the first attempt to quantify the average causal effect of federal aid, for all disasters, on GDP recovery. We found that conditioned on being hit by a disaster, counties that receive federal aid grew faster in the following calendar year than counties that did not.

We compile a robust data set using FEMA and SHELDUS data to construct the universe of

[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 billions whereas FEMA aid amounted to 1.62 billions from 2003 to 2021.

disaster occurrences in the United States from 2003-2021. Our data set includes 1,524 disasters affecting 870 counties in the United States aggregated at the county-year level. We compile county-level descriptors such as population, GDP, unemployment, bank concentration from the Bureau of Economic Analysis (BEA), disaster loan data from the SBA, and IA grants from FEMA.

Our analysis needs to account for potential confounding factors that could affect GDP and federal aid. Ideally, if federal aid was randomly distributed among disaster affected counties, a two way fixed effects model would have recovered the average treatment effect. However, the decision made by FEMA or SBA to grant federal aid is accomplished through an internal selection criterion. In addition to the amount of damages caused by the disaster, there are other factors that can affect the allocation decision. For example, Garrett and Sobel [2007] finds that the decision to extend disaster relief is politically motivated[3]. Furthermore, endogeneity could arise if there are variations in insurance coverage across counties, which could potentially affect the amount of aid that FEMA chooses to grant. Using the two way fixed effects model, we found that the effect of federal aid quantity on GDP recovery is statistically insignificant. The likely explanation could be that FEMA selection criteria allocate the aid proportional to the damage caused by natural disasters to the county. Thus, selection bias may cancel the federal aid's recovery effect.

Due to these issues, we estimate the causal effect using an instrumental variable (IV) approach with county and time fixed effects. We use a new instrument for identification that consists of two variables: 1) county level political competition in non swing states and 2) disaster timing with respect to elections. We argue that swing counties in non swing states affect GDP growth only through the higher likelihood of receiving federal aid when the disaster timing is closer to the election. We used the vote margin in the past elections as a proxy for political competition (swingness) at the county level.

For the exogeneity condition, we argue that this instrument is exogenous in non-swing states. Even though economic theory predicts positive association between political competition and economic outcomes (Ma and McLaren [2018], Besley et al. [2010]), we argue that the incentive for the political party to perform better disappears in a non-swing state. This is due to the presidential election set up in the US states, where the winning state wins all the seats irrespective of the electoral district's result. 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. Compared to counties in

[3] Swing states and those with representation on the FEMA committee receive more aid than their counterparts

swing states, the candidate's extra effort can make a difference in voting pattern for that county, potentially affecting the state decision at the margin. We confirmed this hypothesis and found 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 found that swing counties are more likely to obtain higher aid in non swing states, satisfying the relevance condition. We found the effect to be stronger when the disaster timing was closer to the election cycle and strongest a quarter before the election. Interestingly, this effect disappears in the swing states. This could possibly point towards the heterogeneity in the way swing and non swing states plan election strategy. 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 found that a 1% increase in federal aid, on average, results in a 0.03% point increase in the local GDP growth rate for the next calendar year. Extending the analysis to the long run, we did not find evidence for the effect of federal aid on GDP recovery beyond the calendar year following the disaster occurrence.

This paper contributes to three major avenues of research. First, we are the first to estimate the causal effect of federal aid on the recovery of local provinces following a natural disaster. We build our identification strategy using a new IV, which allows us to deal with the problem of endogeniety (previous studies used difference in differences on similar data). The IV can be generalized and used to calculate the effect of other economic variables on county level GDP with respect to the US given that the economic variable is associated with the local political competition. 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] shows 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 received a disaster relief loan. Watson [2021] finds 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.

Roth Tran and Wilson [2025] is the closest to our paper, where they analyze county level data and estimate the impulse responses of the disaster that triggered FEMA aid on economic outcomes. They found that counties that received federal aid post disaster get a long run income boost. Their analysis considered 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 considered all counties that were affected by the disaster and only those made it to the treatment group, which received federal aid. Thus, our estimate can be interpreted as the causal effect of federal aid alone on GDP recovery.

Second, we contribute to the literature on how political competition affects welfare, which is sparsely explored from an empirical point of view. Theoretical work includes Ma and McLaren [2018] who used a simple model to analyze how lack of political competition can lead to policies that hinder economic growth. Besley et al. [2010] empirically showed that the US tariff structure favors industries located in swing states. In our process of building an IV, we discovered some relevant results related to this literature. We believe we are the first to analyze the effect of political competition on GDP growth rate 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 [2007], Stramp [2013]), we are the first to document that this factor is also relevant at the county level. Interestingly, we found 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 swing counties from the election's point of view, whereas swing states uniformly focus on all the counties.

Although the literature on economic recovery post disaster, politics of federal aid, and effects of disaster on the economy are well-developed, our paper brings all these issues together and analyzes them simultaneously. 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, followed by instrument 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.

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)[4], which provides grants for temporary housing, home repair, and other disaster-related expenses not covered by insurance.

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[5]. This paper focuses specifically on the support provided through the Individuals and Households Program (IHP) 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.

[4] 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)

[5] Details about SBA's loan eligibility criteria can be found on https://www.congress.gov/crs-product/R44412

Unlike other FEMA programs such as Public Assistance (PA) or the Hazard Mitigation Grant Program (HMGP) which are distributed to state and local governments for infrastructure repair or mitigation projects, IHP and SBA funds are not allocated automatically. Instead, 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 Small Business Administration (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 affects the aid distribution is unknown to the public, some of the prominent factors can be identified through data. To contextualize, Figure 1 presents the distribution of 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 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. Panel (d) highlights distribution with respect to political competition proxied by votes margin[6]. We observe that county-level vote margins are, on average, lower for counties that receive aid. This suggests that federal aid declarations are also associated with greater political competition. Garrett and Sobel [2007] and Stramp [2013] documented that political factors play a role in the allocation of aid at the state level. However, the figure suggests that the political factor is also relevant at the county level. Apart from these factors, FEMA, on their website, notes that part of the selection criteria depends on the citizenship status, household income and dependents,

[6] $VotesMargin_c = \frac{|Votes_{D,c} - Votes_{R,c}|}{Votes_{D,c} + Votes_{R,c}}$ is the Vote Margin for county c where D refers to Democrat and R refers to Republican.

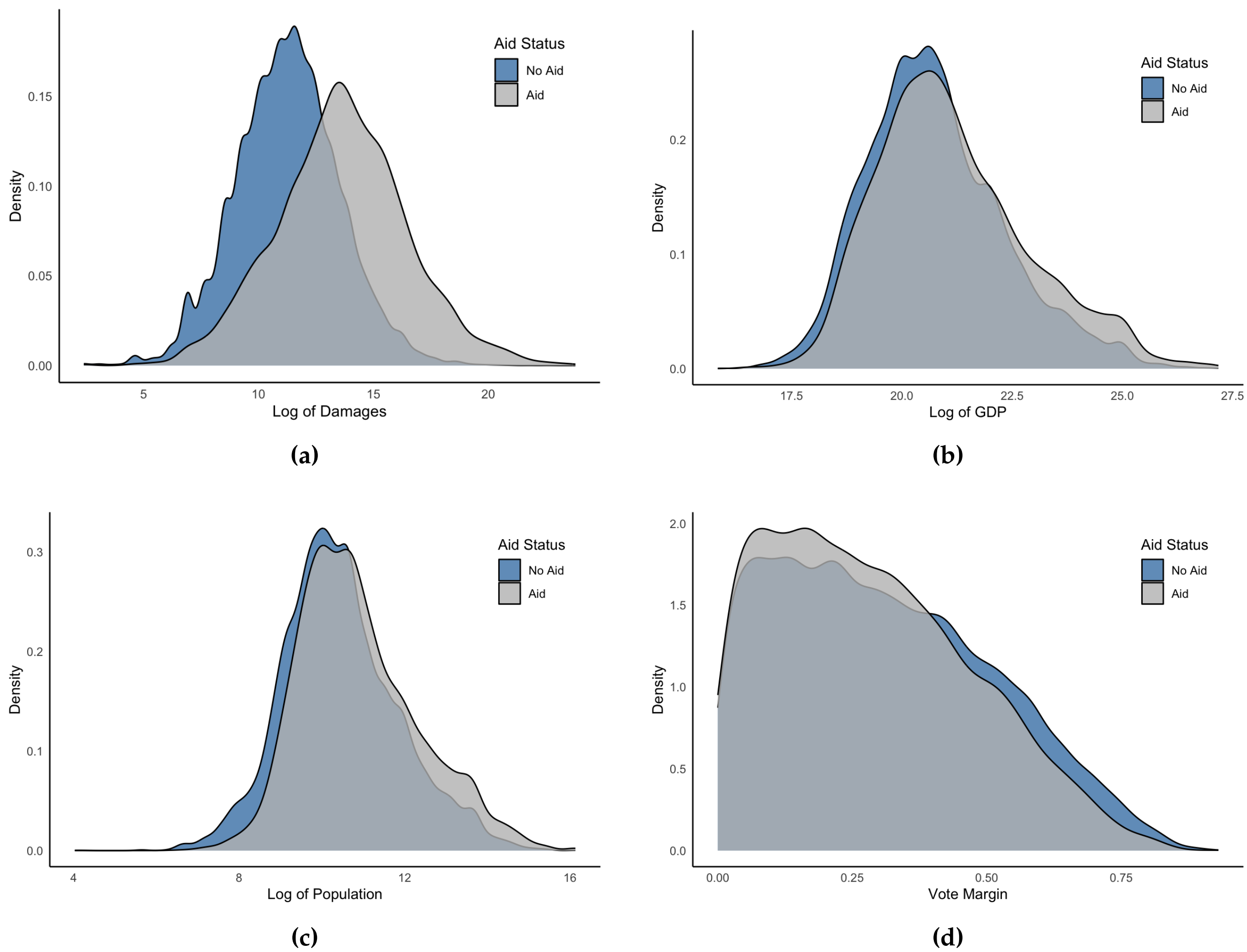


Figure 1: Distribution of county-specific factors by aid status. The gray distribution represents all the counties that were given aid, and the blue represents counties that were not given aid. Panel **(a)** plots the log-transformed total damages reported by SHELDUS. Panel **(b)** plots the distribution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

other insurance payouts, as well as occupancy and identity verification.

2.2 Related Literature

A broad consensus confirms that disasters inflict significant, negative economic shocks in the short run (Hsiang and Jina [2014], Lazzaroni and van Bergeijk [2014]), typically in the form of immediate losses in production, capital, and growth (Klomp and Valckx [2014], Botzen et al. [2019]). However, the long-run economic trajectory following a disaster is far more ambiguous. Some studies suggest that recovery can be sluggish, with permanent negative effects (Hsiang and Jina [2014]). In contrast, another branch of research draws on the creative destruction hypothesis, suggesting that the replacement of destroyed capital with new, more efficient technology 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 DiD approach in their scenario works since the disaster as a treatment is more exogenous[7] than federal aid, which is correlated with the unobserved severity of the damage and the undisclosed selection criteria. Constructing comparable groups of counties that received varying levels of federal aid conditional on being hit by a disaster is more challenging.

Another parallel stream of literature draws upon the political economy that underpins economic growth. A large body of literature finds that political competitiveness is positively associated with economic outcomes, primarily because it creates strong political accountability (Besley et al. [2010], Ma and McLaren [2018]). 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 agendas or rent-seeking and towards

[7] 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.

better governance and public goods delivery. Our paper argues that the incentive to improve economic outcomes due to political competition can disappear at the county level based on the status of the state due to the unique winner-takes-all electoral system in the US.

Similarly, the 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 [2007], 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 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 build on this literature by exploring how political competition of state mediates the allocation of federal aid at the county level from the election strategy point of view.

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. 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

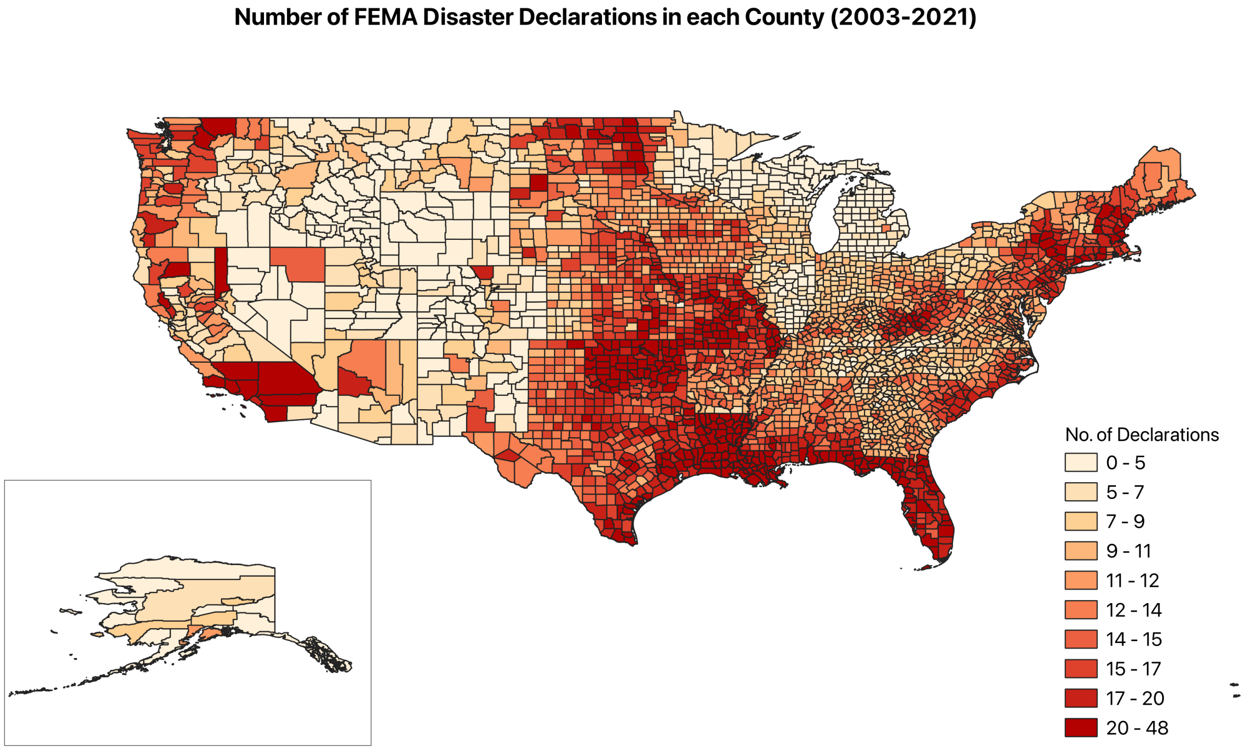


Figure 2: Spatial Distribution of FEMA Disaster Declarations across the United States.

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[8]. We later use a disaster-quarter level panel, constructed only from FEMA aid data, to analyze results at a more granular level as well.

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.[9] In addition to low-interest loans, individuals residing in federally declared 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,

[8] Sources and Frequency of all variables can be found in Table A.4

[9] Not all damages are approved for compensation by the SBA. Individuals must submit loan applications, which 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%.

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.

Table 1: Summary Statistics for all Variables

Variable	Mean	SD	Min	Median	Max
Unemployment Insurance	31,930,503	247,019,086	1,000	3,819,000	31,503,026,000
Number of Jobs	60,705	210,683	53	125,57	6582546
Population	104,003	330,104	55	26,721	10123521
Damages	1039,488	53,819,009	0	0	11750135000
Income per Capita	37,476	12,603	11,522	35,232	318,297
Total Applications	91	3,027	0	0	615,608
Election Spending	35,495	1,798,985	0	0	535,041,907
Votes Margin	0.32	0.21	0.00	0.30	0.94
County GDP	4,787,279,251	20,936,953,585	7,468,000	787,464,000	647,355,553,000
Records	1.26	2.73	0	0	186

We obtain county-level annual outcome data from the Bureau of Economic Analysis (BEA), including indicators on households, businesses, population, unemployment, and production 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 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. Our final dataset is a panel at the county-quarter level, covering the period from Q1 2003[10] to Q4 2021. This time frame is chosen based on consistent availability of both our disaster-related data and our primary economic outcomes from BEA.

Table 1 presents the summary statistics for our final panel dataset, which spans 1,524 disasters affecting 870 counties (total observations: 224,463). Among our control variables, Unemployment Insurance is defined as the financial assistance provided to involuntarily unemployed individuals by the government. Total Application refers to the number of FEMA aid applications submitted by the county, which allows us to control for potential cultural or regional differences. Election Spending captures campaign expenditures by political parties. Records

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

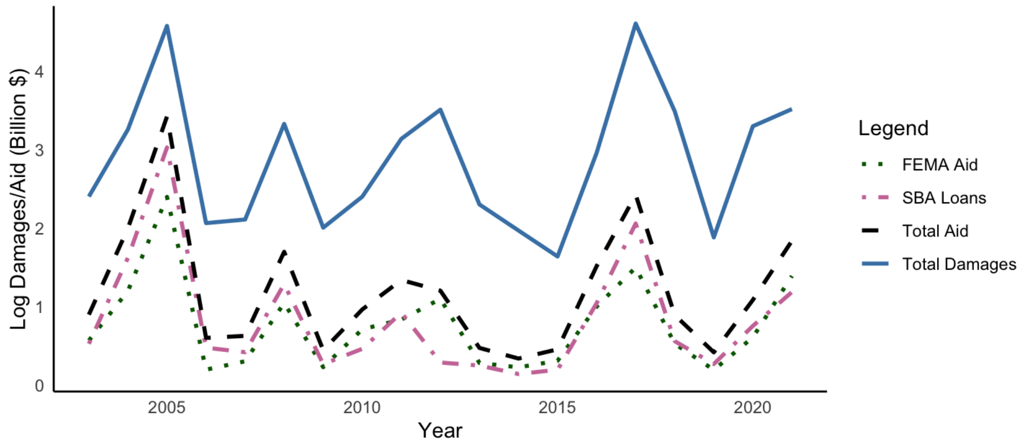


Figure 3: Graph of the total damages caused by natural disasters each year (blue) along with aggregate information such as total funding, FEMA aid, and loans given by the SBA.

serve as a proxy for the number of disasters affecting a county in a given quarter.

As disasters are rare but high-impact events, the median county-quarter experiences zero damages and zero aid applications. However, the mean damage is $1.04 million, indicating a highly right-skewed distribution. This motivates our use of log-transformations in the subsequent analysis. Our outcome and control variables also show substantial variation. The average county-quarter in our sample has a population of 104,003 and a quarterly GDP of $4.79 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, which is essential for our identification strategy.

Figure 3 shows the severity of the disasters over the years, with 2017 being the hardest-hit year at $99 billion dollars worth of damages, 95.2% of which is made up of Hurricanes. Out of the total, 13.2% of all disaster damages on average were covered by FEMA and SBA funding. Insurance also did not cover the rest of the coverage; a recent report by Dixon et al. [2020] shows that local governments are under-insured on average and only receive 28% of repair costs. This significant funding gap leaves ample room for external funding, through aid and low-interest loans provided by FEMA and SBA, respectively, to help with local recovery efforts.

4 Analysis and Results

4.1 Baseline Specification

We begin with the two-way fixed-effects 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 time-invariant characteristics of a county such as geographic vulnerability to disasters, long-run economic composition, and baseline institutional capacity. The dependent variable $\Delta \log(\text{GDP})_{c,t+}$ denotes the annual GDP growth rate in the next calender year for county c. It means that irrespective of in which quarter of the current calender year the disaster occurs, GDP growth rate is calculated considering the first and the fourth quarter of the next calender year. For example, GDP recovery period will be defined as the immediate next 4 quarters if the disaster occurs in the fourth quarter of current calendar year. Similarly, the GDP recovery period will be defined as the 4 quarters following the 3 quarters gap post disaster if the disaster occurs in the first quarter of current calender year. Following this logic, the coefficient of interest β can be interpreted as the average effect of federal aid on GDP recovery where the recovery period spans the next eight quarters. To facilitate understanding, let β_t be the effect of federal aid on GDP recovery where t represents the number of quarters between the disaster timing and the start of the recovery period. For example, $t = 0$ means that the disaster occurred in the fourth quarter of the current calendar year and the recovery period starts immediately in the first quarter of the next calendar year. One potential interpretation of β could be that it can be written as a weighted average of β_t as $\beta = \sum_{t=0}^{3} w_t \beta_t$. Since disasters are more likely to occur in the second or third quarter of the calendar year, the weights will be higher for β_t where $t = 2$ or 3.

The results for Eq. 1 are presented in panel (1) of Table 2. We observe no significant effect of federal aid on GDP growth rates. This likely arises from the selection bias in the allocation of federal aid across disasters and counties. FEMA and SBA tend to channel more assistance towards counties that experience greater disaster severity, which are also the counties most likely to exhibit slower economic recovery in the absence of federal aid. Consequently, the negative selection biases the estimated relation downward. Under our hypothesis that disaster aid has a positive effect on GDP recovery, this selection bias may offset the true positive impact of aid, resulting in the observed insignificant coefficients under all aid specifications of the two-way fixed effects estimation.

We also estimate Eq. 1 by considering 1) SBA loans only (in panel (2)), representing approved disaster loans to households and firms, and FEMA aid only (in panel (3)), representing grants disbursed through IHP. We used clustering at the county level for these three regressions. The FEMA data provide us with unique disaster id which SBA data set is missing. Thus, we re-estimate Eq. 1 with FEMA aid only with clustering as the disaster level. The effect is still insignificant in all these settings.

4.2 Instrumental Variable

Our identification strategy aims to use the variation in political competitiveness between counties as an instrument for the amount of federal disaster aid received. Several studies suggest that politically competitive areas are more likely to receive a disproportionate share of government funds (Garrett and Sobel [2007], Stramp [2013]), and we believe that the same should hold true for federal disaster assistance. Moreover, we believe that this effect is stronger when a disaster occurs closer to a presidential election. Thus, we start with considering the interaction of 1) votes margin in the past elections at a county level and 2) timing of disaster with respect to election as our instrumental variable.

The relevance condition for political competition can be backed by economic theory. The swing counties can get preferential treatment in getting federal aid compared to non swing counties. We can expect the effect to be stronger when the timing of the disaster is closer to the timing of the elections (which can be argued as exogenous). Politicians may exploit the recency bias among the voters and reward the swing county with higher federal aid only closer to elections. However, the exogeneity condition for political competition is difficult to defend, as there is a great literature on how political competition is associated with the welfare of the economy. Politicians have incentive to choose welfare maximizing policy compared to rent seeking when the election decision is not certain (Besley et al. [2010]). To test this concern of endogeneity, we estimate the two-way fixed effects model as

Table 2: Regression of GDP Growth on Federal Assistance

Dependent Variable:	$\Delta \log(\text{GDP})_{t+8,t+4}$			
Data:	Aggregate (1)	SBA (2)	FEMA (3)	FEMA (4)
Log Aid	8.12×10^{-5}	0.0001	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0004)	(0.0004)
Log Unemployment Insurance	-0.0181***	-0.0179***	-0.0170***	-0.0170***
	(0.0019)	(0.0019)	(0.0020)	(0.0013)
Log Number of Jobs	-0.0890***	-0.0919***	-0.0976***	-0.0976***
	(0.0132)	(0.0130)	(0.0139)	(0.0066)
Log Population	0.0531***	0.0568***	0.0544***	0.0544***
	(0.0173)	(0.0169)	(0.0186)	(0.0112)
Log Damages	0.0001	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log Income per Capita	-0.1591***	-0.1576***	-0.1565***	-0.1565***
	(0.0123)	(0.0124)	(0.0129)	(0.0067)
Log Applications	-0.0002	-0.0003	0.0001	0.0001
	(0.0003)	(0.0002)	(0.0009)	(0.0009)
Log Records	0.0004	4.13×10^{-5}	-0.0002	-0.0002
	(0.0006)	(0.0006)	(0.0006)	(0.0009)
Log Election Spending	-0.0001	-0.0001	-0.0002***	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(6.3×10^{-5})
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Disaster FE	No	No	Yes	Yes
County Clustering	Yes	Yes	Yes	No
Disaster Clustering	No	No	No	Yes
Observations	82,849	81,313	84,775	84,775
R^2	0.14960	0.15061	0.18598	0.18598
Within R^2	0.02023	0.02047	0.01956	0.01956

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Regressing GDP Growth on Votes Margin

Dependent Variable:	$\Delta \log(\text{GDP})_{t+8,t+4}$		
Panel:	All Data	Disasters	No Disasters
	(1)	(2)	(3)
Margin	-0.0329***	-0.0520***	-0.0208**
	(0.0065)	(0.0066)	(0.0084)
Log Unemployment Insurance	-0.0186***	-0.0173***	-0.0191***
	(0.0017)	(0.0018)	(0.0021)
Log Number of Jobs	-0.0929***	-0.0987***	-0.0932***
	(0.0141)	(0.0132)	(0.0168)
Log Population	0.0424**	0.0450***	0.0427**
	(0.0166)	(0.0170)	(0.0204)
Log Income per Capita	-0.1542***	-0.1555***	-0.1566***
	(0.0110)	(0.0124)	(0.0128)
Log Election Spending	0.0001	-0.0002	0.0003**
	(0.0001)	(0.0001)	(0.0001)
Quarter FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	200,271	81,313	118,958
Within R^2	0.02174	0.02227	0.02181

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

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

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 3. 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 considered the subset of the data where 1) we considered only those counties and periods where disasters occurred (panel (2)) and 2) the subset of counties and periods where there were no disasters (panel (3)). Panel (3) allows us to isolate the possible direct association between political competition and GDP growth, bypassing aid entirely, as aid is only provided in the case of a disaster. Thus, Panel (3) is a better specification for testing exogeneity condition. The effect is still negative and significant. These results provide evidence that the exogeneity condition is violated. Especially when the result holds for the non-disaster subset, where we obtain the direct association between political competition and GDP growth rate.

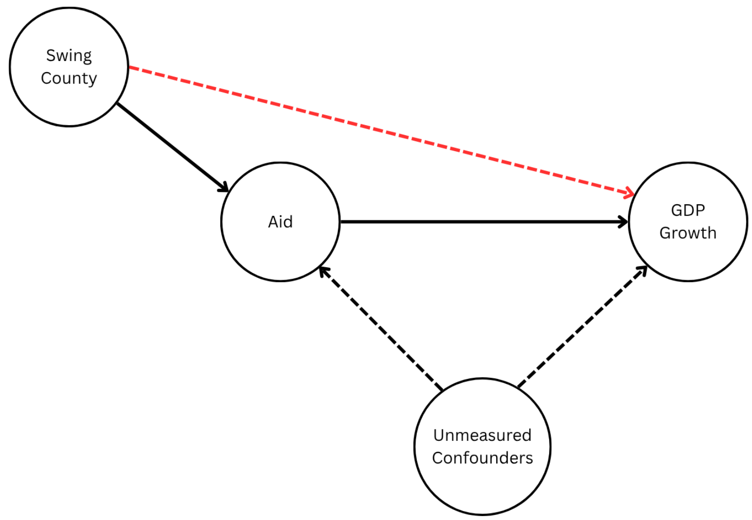


Figure 4: Exogeneity of IV

4.3 Exogeneity Condition: Political Competition and GDP Growth Rate

To overcome this endogeneity concern, 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 robustness, we also use a cutoff criterion for robustness where we define a state as swing if the difference in vote shares of the two major parties is less than 10%, 15% and 20%. In non swing states, county-level political competition does not influence presidential election outcomes, as electoral votes are allocated on a winner-takes-all basis and statewide vote shares determine the outcome. Consequently, local politicians do not have any incentive to strategically improve the economic conditions of the county in response to electoral competitiveness. This ensures that, within non-swing states, political competition affects economic outcomes only through the aid channel, satisfying the exclusion restriction required for our IV strategy. We illustrate this mechanism in Figure 4 where we attempt to block the red path between swing county and GDP growth by restricting our analysis to non-swing states. Thus, we intend to interpret our instrument as follows: the political competition among counties in non swing states affects GDP growth rate only through federal aid when disaster timing is close to elections.

We assess the exogeneity condition by examining whether county-level political competition directly influences GDP growth in periods when disaster aid cannot operate as a channel. To do this, we regress GDP growth on county vote margins using only the subset of 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 4.

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 under the winner-takes-all electoral system, county-level political competition does not translate into differential economic performance. These results support the exogeneity of our political-competition instrument when restricting the analysis to non-swing states.

4.4 Relevance Condition: Political Competition and Federal Aid

For the first of our 2SLS estimation, we regress log of Aid on the county level vote margin directly without any time dynamic according to Equation 3. Here, α provides the estimated impact of political competition on the allocation of disaster aid during a disaster. We then estimate Equation 3 on the subset of data with disasters for all states, swing states, and non-swing states. The results of this estimation are presented in Table 5.

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

We observe that the effect of political competition on disaster aid is negative and statistically significant when we estimate the model using all states, and more importantly, when we restrict the sample to non-swing states. In both cases, counties with tighter vote margins receive substantially more federal assistance following a disaster. Surprisingly, the relationship is statistically insignificant within swing states, suggesting meaningful heterogeneity in how political incentives shape 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. Whereas, swing states may pursue a more uniform allocation strategy given that the entire state is electorally competitive.

Although this specification yields a relevant first stage when using county-level vote margin

Table 4: Estimated impact of political competition on GDP growth for the subset of data with no disasters.

Dependent Variable:	$\Delta \log(\text{GDP})_{t+8,t+4}$	
	Swing States	Non-Swing States
Model:	(1)	(2)
Panel A: Swing State Historical Classification		
Margin	-0.0443***	-0.0099
	(0.0093)	(0.0115)
Observations	38,883	80,075
Avg. No. of States	15	32.6
Panel B: Swing State Cutoff Classification (cutoff = 0.10)		
Margin	-0.0287**	-0.0194
	(0.0113)	(0.0130)
Observations	46,621	72,337
Avg. No. of States	16.3	31.3
Panel C: Swing State Cutoff Classification (cutoff = 0.15)		
Margin	-0.0258*	-0.0132
	(0.0148)	(0.0140)
Observations	63,852	55,106
Avg. No. of States	23.5	24.1
Panel D: Swing State Cutoff Classification (cutoff = 0.20)		
Margin	-0.0257**	0.0131
	(0.0101)	(0.0202)
Observations	84,190	34,768
Avg. No. of States	31	16.6
Quarter FE	Yes	Yes
County FE	Yes	Yes

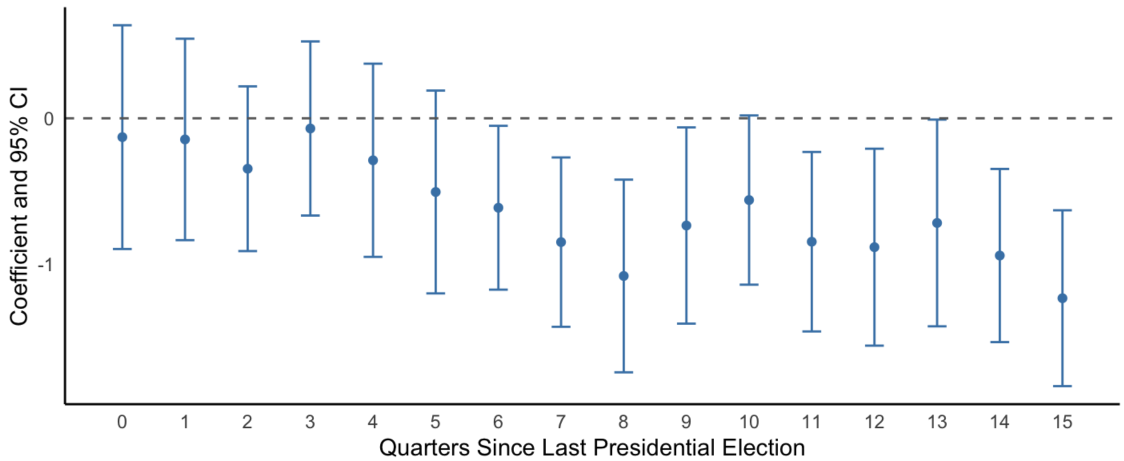
Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Regression of Disaster Aid on Political Competition

Dependent Variable:	Log Aid		
	All Data	Swing	Non-Swing
Model:	(1)	(2)	(3)
Variables			
Margin	-0.3382**	0.0791	-0.6788***
	(0.1584)	(0.2571)	(0.2050)
Log Unemployment Insurance	0.1300***	0.0472	0.0477
	(0.0395)	(0.0629)	(0.0573)
Log Number of Jobs	-0.0873	-0.6757	0.1657
	(0.2410)	(0.4425)	(0.2984)
Log Population	-0.6911**	-0.3722	-0.6090*
	(0.3048)	(0.5765)	(0.3520)
Log Damages	0.0567***	0.0701***	0.0496***
	(0.0065)	(0.0098)	(0.0084)
Log Income per Capita	0.1466	0.3447	-0.0422
	(0.1981)	(0.3726)	(0.2340)
Log Total Applications	1.797***	1.747***	1.811***
	(0.0106)	(0.0155)	(0.0139)
Log Records	0.0392*	0.1235***	-0.0161
	(0.0234)	(0.0374)	(0.0301)
Log Election Spending	-0.0034	-0.0146**	0.0086
	(0.0055)	(0.0073)	(0.0080)
Fixed-effects			
Quarter FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Fit statistics			
Observations	89,237	35,137	54,100
R^2	0.60102	0.57444	0.61959
Within R^2	0.54835	0.49516	0.56378

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

Figure 5: Coefficients for the first stage regression. Data restricted to non swing states.



as the instrument, we extend our IV strategy to incorporate the timing of the next presidential election, allowing the strength of political incentives to vary systematically over the electoral cycle. Our modified first-stage equation is therefore given by Equation 4, which we estimate only for the subset of non-swing states, consistent with the exogeneity conditions established earlier. Table 6 presents the results for this estimation.

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

Here the interaction between county level vote margin and dummies for the number of quarters with respect to the last presidential elections captures how the strength of the effect of political competition on aid evolves over the electoral cycle, which allows 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.

Figure 5 illustrates how the effect of political competition on disaster aid varies systematically throughout the presidential electoral cycle. The state conducts their own gubernatorial and legislative elections around 8^{th} quarter, and the presidential election happens after 15^{th} quarter in the graph. We observe that in the quarters immediately preceding the election, the effect of directing disaster aid toward politically competitive counties increases sharply. The results are consistent with the idea that policymakers 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. In contrast, immediately after an election, when both federal and state-

Table 6: First Stage IV regression with different Aid categories

Dependent Variable:	Log Aid			
Data:	Aggregate	SBA	FEMA	FEMA
	(1)	(2)	(3)	(4)
Margin × $\text{PostElection}_{=0}$	-0.1292	0.6721	-0.2103***	-0.2103
	(0.3911)	(0.4502)	(0.0693)	(0.1689)
Margin × $\text{PostElection}_{=1}$	-0.1449	-0.3655	-0.0942	-0.0942
	(0.3521)	(0.3480)	(0.0717)	(0.1065)
Margin × $\text{PostElection}_{=2}$	-0.3457	-0.4835	-0.0858	-0.0858
	(0.2880)	(0.3042)	(0.0707)	(0.1170)
Margin × $\text{PostElection}_{=3}$	-0.0699	-0.1286	0.1543	0.1543
	(0.3043)	(0.3144)	(0.0985)	(0.1407)
Margin × $\text{PostElection}_{=4}$	-0.2879	-0.2627	-0.1401	-0.1401
	(0.3377)	(0.3421)	(0.0936)	(0.1670)
Margin × $\text{PostElection}_{=5}$	-0.5052	-0.6004*	-0.0105	-0.0105
	(0.3546)	(0.3560)	(0.0956)	(0.1189)
Margin × $\text{PostElection}_{=6}$	-0.6132**	-0.7510**	-0.1593**	-0.1593
	(0.2864)	(0.2981)	(0.0703)	(0.1440)
Margin × $\text{PostElection}_{=7}$	-0.8489***	-1.032***	-0.0292	-0.0292
	(0.2960)	(0.3058)	(0.0625)	(0.0981)
Margin × $\text{PostElection}_{=8}$	-1.081***	-0.4830	-0.1053	-0.1053
	(0.3369)	(0.3433)	(0.0674)	(0.1192)
Margin × $\text{PostElection}_{=9}$	-0.7351**	-0.7450**	-0.2589***	-0.2589
	(0.3430)	(0.3501)	(0.0971)	(0.2342)
Margin × $\text{PostElection}_{=10}$	-0.5605*	-0.9491***	-0.0925	-0.0925
	(0.2958)	(0.3184)	(0.0845)	(0.1324)
Margin × $\text{PostElection}_{=11}$	-0.8462***	-1.2630***	-0.1932**	-0.1932
	(0.3137)	(0.3343)	(0.0861)	(0.1786)
Margin × $\text{PostElection}_{=12}$	-0.8836**	0.4010	-0.1286*	-0.1286
	(0.3443)	(0.3879)	(0.0698)	(0.1291)
Margin × $\text{PostElection}_{=13}$	-0.7176**	-0.7361*	-0.0536	-0.0536
	(0.3614)	(0.3847)	(0.0762)	(0.1123)
Margin × $\text{PostElection}_{=14}$	-0.9409***	-0.8832***	-0.1076*	-0.1076
	(0.3027)	(0.3194)	(0.0653)	(0.1143)
Margin × $\text{PostElection}_{=15}$	-1.2340***	-0.7033**	0.0067	0.0067
	(0.3074)	(0.3357)	(0.0798)	(0.1007)
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Disaster FE	No	No	Yes	Yes
County Clustering	Yes	Yes	Yes	No
Disaster Clustering	No	No	No	Yes

c: County Level Clustering; d: Disaster Level Clustering
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

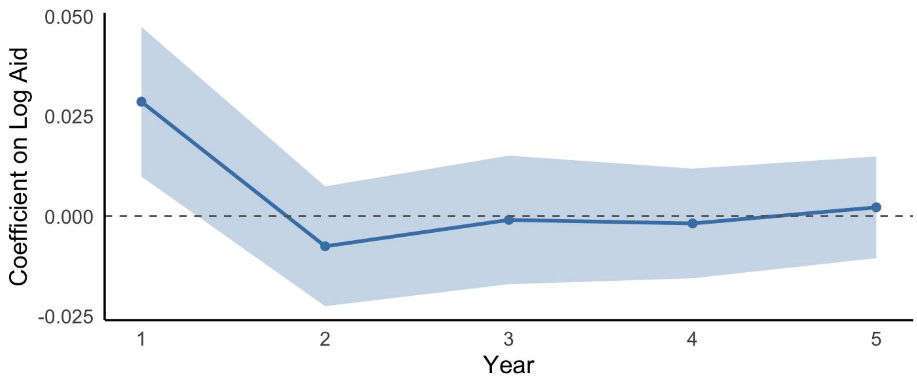


Figure 6: Long term impact of Disaster Aid on GDP growth rate

level electoral incentives are at their lowest, the effect of political competition on aid allocation becomes weaker.

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, as specified in Equation 5,

$$\Delta \log(\text{GDP})_{c,t+8,t+4} = \beta \widehat{\log \text{Aid}_{c,t}} + \gamma \mathbf{X}_{c,t} + \delta_c + \tau_t + \epsilon_{c,t} \tag{5}$$

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 0.0286 implies that a 1% increase in disaster aid leads to a 0.0286 percentage-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, four-year, and five-year-ahead GDP growth rates. The results of this estimation can be observed in Figure 6 where we plot the coefficients of each of these regressions. We found 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 persistent medium or long term effects on county-level economic growth.

Table 7: Second Stage IV Regression

Dependent Variable:	$\Delta \log(\text{GDP})_{t+8,t+4}$
Model:	(1)
Variables	
$\widehat{\text{Log Aid}}$	0.0286***
	(0.0095)
Log Unemployment Insurance	-0.0197***
	(0.0035)
Log Number of Jobs	-0.1161***
	(0.0177)
Log Population	0.0833***
	(0.0237)
Log Damages	-0.0012**
	(0.0006)
Log Income per Capita	-0.1610***
	(0.0169)
Log Total Applications	-0.0525***
	(0.0173)
Log Records	0.0019
	(0.0012)
Log Election Spending	-0.0004
	(0.0003)
Fixed-effects	
Quarter FE	Yes
County FE	Yes
Fit statistics	
Observations	49,323
R^2	0.14440
Within R^2	0.02159

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

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 2003–2021, we study how FEMA Individual Assistance grants and SBA disaster loans affect post-disaster GDP growth. Conditioning on disaster exposure, we show that counties receiving federal aid grow faster in the year following a disaster relative to affected counties that do not receive aid.

These findings contribute to the literature in several ways. First, we provide the first estimate of the causal effect of federal disaster aid—isolated from the effect of disasters themselves—on aggregate local economic recovery. Second, our results add new empirical evidence to the literature on political competition by documenting meaningful variation at the county level and showing how it shapes policy outcomes. Third, we uncover evidence that political considerations affect the allocation of federal aid at a finer geographic scale than previously studied, with distinct strategies employed in swing versus non-swing states.

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. Future research could explore the mechanisms behind the short-run gains—such as labor market adjustments, business survival, or credit constraints—and examine whether complementarities with insurance coverage or state-level policies can enhance the durability of recovery.

Overall, this paper bridges the literature on disaster economics, political economy, and public finance, offering a unified empirical framework to understand how political incentives shape disaster aid and how that aid, in turn, affects local economic outcomes. Looking forward, the research opens several avenues for deeper investigation. For example, exploring more granular aspects of how aid affects different sectors within local economies might offer tailored insights for sector-specific recovery strategies.

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Appendix A: Other Specifications

Table A.1: Second Stage IV regression with different Aid categories

Dependent Variable:	$\Delta \log(\text{GDP})_{t+8,t+4}$			
Data:	Aggregate^c (1)	SBA^c (2)	FEMA^c (3)	FEMA^d (4)
$\widehat{\text{Log Aid}}$	0.0286***	0.0133**	0.0824**	0.0824**
	(0.0095)	(0.0055)	(0.0395)	(0.0377)
Log Insurance	-0.0197***	-0.0213***	-0.0158***	-0.0158***
	(0.0035)	(0.0033)	(0.0036)	(0.0032)
Log Population	0.0832***	0.0829***	0.0504*	0.0504*
	(0.0237)	(0.0232)	(0.0285)	(0.0260)
Log Damage	-0.0012**	-0.0011*	0.0009**	0.0009
	(0.0006)	(0.0006)	(0.0004)	(0.0007)
Log Total Applications	-0.0525***	-0.0166**	-0.1531**	-0.1531**
	(0.0173)	(0.0066)	(0.0738)	(0.0696)
Log Election Spending	-0.0004	-0.0003	-0.0004*	-0.0004*
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Disaster FE	No	No	Yes	Yes

c: County Level Clustering; d: Disaster Level Clustering
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.2: TWFE regression with different Aid categories

Dependent Variable:	$\Delta \log(\text{GDP})_{t+8,t+4}$			
Data:	Aggregate	SBA	FEMA	FEMA
	(1)	(2)	(3)	(4)
Log Aid	8.12×10^{-5}	0.0001	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0004)	(0.0004)
Log Unemployment Insurance	-0.0181***	-0.0179***	-0.0170***	-0.0170***
	(0.0019)	(0.0019)	(0.0020)	(0.0013)
Log Number of Jobs	-0.0890***	-0.0919***	-0.0976***	-0.0976***
	(0.0132)	(0.0130)	(0.0139)	(0.0066)
Log Population	0.0531***	0.0568***	0.0544***	0.0544***
	(0.0173)	(0.0169)	(0.0186)	(0.0112)
Log Damages	0.0001	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log Income per Capita	-0.1591***	-0.1576***	-0.1565***	-0.1565***
	(0.0123)	(0.0124)	(0.0129)	(0.0067)
Log Applications	-0.0002	-0.0003	0.0001	0.0001
	(0.0003)	(0.0002)	(0.0009)	(0.0009)
Log Records	0.0004	4.13×10^{-5}	-0.0002	-0.0002
	(0.0006)	(0.0006)	(0.0006)	(0.0009)
Log Election Spending	-0.0001	-0.0001	-0.0002***	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(6.3×10^{-5})
Quarter FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Disaster FE	No	No	Yes	Yes
County Clustering	Yes	Yes	Yes	No
Disaster Clustering	No	No	No	Yes
Observations	82,849	81,313	84,775	84,775
R^2	0.14960	0.15061	0.18598	0.18598
Within R^2	0.02023	0.02047	0.01956	0.01956

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.3: Summary Statistics of Controls

Variable	N	Mean	SD	Min	Median	Max
Unemployment Insurance	223,299	3.19e+07	2.47e+08	1.00e+03	3.82e+06	3.15e+10
Number of Jobs	223,299	6.07e+04	2.11e+05	5.30e+01	1.26e+04	6.58e+06
Population	223,299	1.04e+05	3.30e+05	5.50e+01	2.67e+04	1.01e+07
Damages	223,299	1.04e+06	5.38e+07	0.00e+00	0.00e+00	1.18e+10
Income per Capita	223,299	3.75e+04	1.26e+04	1.15e+04	3.52e+04	3.18e+05
Total Applications	223,299	9.14e+01	3.03e+03	0.00e+00	0.00e+00	6.16e+05
Records	223,299	1.26e+00	2.73e+00	0.00e+00	0.00e+00	1.86e+02
Election Spending	223,299	3.55e+04	1.80e+06	0.00e+00	0.00e+00	5.35e+08
Votes Margin	223,299	3.18e-01	2.05e-01	7.15e-05	2.96e-01	9.38e-01
County GDP	223,299	4.79e+09	2.09e+10	7.47e+06	7.87e+08	6.47e+11

Other Tables

Table A.4: 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