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Abstract

Using a novel dataset on U.S. natural disasters and high-frequency measures of economic activity, we evaluate the effectiveness of federal disaster assistance. Exploiting quasi-random variation in whether aid from the Federal Emergency Management Agency is granted or denied, we compare otherwise similar events. States receiving aid recover within 20 weeks, whereas denied states face deeper and more persistent contractions. Recovery is stronger when aid is timely and generous, and includes direct transfers. Pre-disaster mitigation lowers future disaster frequency and costs, while stronger fiscal capacity enhances resilience by enabling governments to sustain post-disaster recovery.

Keywords: disaster relief (FEMA), post-disaster economic recovery, fiscal preparedness, disaster mitigation.

JEL classification: H84, Q54, E62, H72, R11.

Resumen

Utilizando una novedosa base de datos sobre desastres naturales en Estados Unidos y medidas de alta frecuencia de la actividad económica, evaluamos la efectividad de la asistencia federal ante los desastres. Aprovechando la variación cuasialeatoria en la concesión o denegación de ayudas por parte de la Agencia Federal para el Manejo de Emergencias (FEMA, por sus siglas en inglés), comparamos eventos que, por lo demás, son similares. Los Estados que reciben ayuda se recuperan en un plazo de 20 semanas, mientras que aquellos a los que se les deniega enfrentan contracciones más profundas y persistentes. La recuperación es más rápida cuando la ayuda llega a tiempo, es generosa e incluye transferencias directas. La mitigación previa al desastre reduce la frecuencia de los desastres y los costes futuros, mientras que una mayor capacidad fiscal fortalece la resiliencia al permitir que los gobiernos sostengan la recuperación posterior al desastre.

Palabras clave: ayuda en caso de desastres (FEMA), recuperación económica tras desastres, preparación fiscal, mitigación de desastres.

Códigos JEL: H84, Q54, E62, H72, R11.

I. Introduction

The increasing frequency and severity of natural disasters—often intensified by climate change—pose significant challenges for governments globally. In the United States, federal disaster assistance, particularly through the Federal Emergency Management Agency (FEMA), plays a central role in supporting state-level recovery efforts. FEMA, financed by the U.S. Congress through the federal *Disaster Relief Fund* (DRF), provides disaster aid through two main programs: *Public Assistance* (PA) for debris removal, emergency measures, and public infrastructure, and *Individual Assistance* (IA) for households. Despite substantial federal involvement, concerns remain about the effectiveness of such aid in fostering timely and sustained economic recovery.

A growing literature examines the macroeconomic effects of natural disasters and the role of public policy in recovery. Deryugina (2017) documents persistent fiscal drag in U.S. counties following hurricanes, driven by both disaster aid and increased non-disaster transfers, while broader evidence shows that disaster impacts depend on institutional quality and fiscal capacity, not only physical severity (Cavallo and Noy, 2011; Strobl, 2012). Consistent with this view, Grosse-Steffen et al. (2025) find greater shock absorption under fiscal rules, Costa and Hooley (2025) document faster recoveries in OECD countries with more fiscal space, and Canova and Pappa (2022) link state-level fiscal responses to recovery dynamics. Related work highlights the role of preparedness and mitigation (Hsiang and Jina, 2014; Deryugina et al., 2018), while Dibiasi et al. (2026) show that government spending multipliers are larger during disaster periods. Relative to this literature, we contribute by using weekly data to estimate the marginal effects of federal disaster assistance and by analyzing how aid composition and state fiscal characteristics shape post-disaster dynamics.

More specifically, we contribute by empirically assessing the effectiveness of federal disaster assistance across U.S. states, exploiting variation in whether FEMA aid is granted or denied. We focus on storms and floods, the most frequent and comparable natural disasters in the United States. While aid allocation is not fully random—denied disasters tend to exhibit lower average economic impacts—we identify a subset of disasters that exceed FEMA's per capita damage threshold, its primary eligibility criterion, yet are nonetheless denied assistance.

We show that these denial decisions are systematically associated with political alignment and procedural factors, but are not correlated with states' pre-disaster economic fundamentals, fiscal capacity, or insurance coverage. Leveraging this quasi-random variation among disasters of comparable severity, we identify the marginal effect of federal disaster assistance.

To capture post disaster economic dynamics, we use a high frequency index of weekly economic activity complemented by weekly initial jobless claims to trace short term impacts and recovery paths. We also explore the role of fiscal preparedness, measured via hazard mitigation spending, fiscal space, rainy day funds, and budgetary rules, as a determinant of resilience.

Our results are robust to alternative measures of economic activity. Using quarterly data on gross state product to assess the effects of federal assistance yields similar conclusions, as does employing labor market indicators such as weekly initial jobless claims instead of the weekly economic activity index. In addition, fuzzy regression discontinuity estimates confirm our baseline findings: federal assistance mitigates and gradually reverses the adverse economic effects of disasters.

Our findings indicate that timely and generous federal aid significantly improves post-disaster recovery, particularly when both public and individual assistance are provided. Additionally, we show that pre-disaster mitigation and robust fiscal frameworks lower the economic costs of disasters and enhance recovery outcomes. These insights are critical for designing resilient and equitable disaster response and adaptation policies in a world where climate-related disasters are becoming increasingly frequent and severe.

The remainder of the paper is organized as follows: Section II describes the data; Section III outlines the empirical methodology; Section IV presents results and robustness checks; and Section V concludes.

II. Data and Summary Statistics

A. Data Sources

Our primary data source for natural disasters is FEMA, a U.S. federal agency under the Department of Homeland Security responsible for coordinating disaster response and recovery. We construct a novel dataset on disaster severity and details on federal assistance by merging FEMA's publicly available disaster declaration database with information extracted from Preliminary Damage Assessments (PDAs)—standardized reports jointly prepared by FEMA and state, local, tribal, and territorial (SLTT) authorities during the disaster declaration process.

The declaration process follows a standardized sequence (Figure D1). After a disaster, FEMA and SLTT authorities conduct a joint Preliminary Damage Assessment (PDA) to document impacts and estimate eligible needs. Based on the assessment, the governor or Tribal Chief Executive may request a major disaster declaration within 30 days of the incident's onset or, if later, within 30 days of the end of the incident period, subject to extensions. FEMA evaluates the request using program specific criteria, including Individual Assistance factors and Public Assistance per capita indicators, and submits a recommendation to the President, who approves or denies the declaration under the Stafford Act.[1]

[1]FEMA applies criteria set out in 44 C.F.R. § 206.48, including statewide per capita impact, while the President retains full discretion under the Stafford Act (42 U.S.C. §§ 5170, 5191).

This institutional timeline underpins our measurement strategy. PDAs provide standardized severity metrics and precise dates for incidents and requests, for both approved and denied cases, enabling consistent measures of disaster intensity and decision lags across events. Additional institutional background on FEMA is provided in Appendix D.

FEMA's official disaster database includes all major federally supported disasters, providing information on disaster type, location, declaration date, and activated aid programs. These include: (1) Public Assistance (PA) for state and local governments, (2) Individual Assistance (IA) for households, and (3) Hazard Mitigation Assistance to reduce future losses. However, the dataset excludes denied requests and omits key variables such as disaster severity (e.g., economic impact estimates) and the timing and scale of aid disbursement.

To fill these gaps, we extract data from PDAs for all disaster requests—approved and denied—filed between 2006 and 2023. PDAs contain rich, standardized information including disaster type, event and request dates, decision outcomes, estimated public assistance costs, statewide per capita damage estimates, and FEMA's per capita eligibility thresholds.

For denied disasters, PDAs are our sole data source. For approved disasters, we augment FEMA's database with PDA-derived variables such as estimated fiscal impact, aid delay (weeks between event and decision), FEMA's eligibility threshold, approval date, and actual disbursed public assistance. This integration enables consistent construction of key variables across all events, including the timing and scale of federal responses.

To capture high-frequency economic activity, we use the Weekly Economic Conditions Index (ECI) from Baumeister et al. (2024). The ECI, based on a mixed-frequency dynamic factor model, synthesizes multiple dimensions of state-level performance—mobility, labor markets, output, expectations, financial conditions, and household indicators—into a single weekly measure. The index is normalized so that a value of zero indicates state economic conditions consistent with the long-run year-on-year growth rate of U.S. real GDP. This index serves as our primary outcome variable to track the short-run economic impact of disasters and evaluate the effectiveness of federal aid. We also assess the robustness of our main results using weekly initial jobless claims as a high-frequency measure of economic activity. Further details on the ECI's construction and robustness are provided in the Appendix.

B. Summary Statistics on U.S. Natural Disasters

We limit our analysis to storms and floods, which are not only the most commonly occurring natural disasters in the United States but also exhibit a high degree of comparability.[2]

[2]Fernández-Gallardo (2025) documents that storms and floods have accounted for over 80 percent of all natural disasters in the U.S. since 1900. Within our sample of 493 storms and floods, FEMA classifies 400 as storms and 93 as floods, implying that storms constitute just over 80 percent of the storms-and-floods sample.

Table 1 reports summary statistics for key variables used in our analysis, disaggregated by FEMA program status. We present results for three groups: all disasters in the sample, those that received federal assistance (either Public Assistance [PA] alone or both PA and Individual Assistance [IA]), and those that were denied aid.[3] This classification facilitates a comparison of disaster severity, the timing of federal response, and the scale of assistance. The observed patterns reveal systematic differences across groups, shedding light on the characteristics of disasters that receive aid and motivating our empirical identification strategy.

Panel A of Table 1 reports the *statewide per capita impact* (in dollars), which serves as our proxy for initial disaster severity. The baseline sample spans the period from 2006w1 to 2019w52 and excludes the exceptional COVID-19 period. We assess the robustness of our results to the inclusion of this period in a set of sensitivity analyses presented in Figure B4 in the Appendix. The average per capita impact across all disasters is \$4.49. Approved disasters exhibit a higher average impact (\$4.66), while denied events average \$3.21, aligning with FEMA's eligibility criteria that prioritize more severe disasters. Among approved cases, those receiving both Public Assistance (PA) and Individual Assistance (IA) have a markedly higher average impact (\$6.66) than those receiving only PA (\$4.33), consistent with the higher threshold required for IA activation.

Panel B presents the average *lag in federal response*, measured in weeks from the disaster event to the federal decision. For approved disasters, the average lag is 7.42 weeks. Notably, disasters receiving both PA and IA are approved more quickly (4.40 weeks) than those receiving only PA (7.92 weeks), suggesting that more severe disasters may prompt faster federal action. In contrast, denial decisions take significantly longer, averaging 15.5 weeks.[4]

Panel C shows the *total federal assistance per capita* for approved disasters. The average allocation is \$4.66 per capita, but this varies considerably by program: disasters receiving only PA average \$4.13, while those receiving both PA and IA receive nearly double, at \$7.79. This again reflects the greater severity and resource needs of disasters qualifying for both forms of aid.

Overall, the data suggest that federal assistance is generally directed toward higher-impact events, which also receive faster responses and more substantial aid. However, there is considerable within-group variation, with some denied disasters exhibiting severity levels comparable to approved ones. We exploit this quasi-random variation in our empirical strategy to estimate the marginal impact of receiving federal assistance.

[3]FEMA delivers disaster assistance mainly through two programs: *Public Assistance* (PA)—for debris removal, emergency protective measures, and damaged public facilities—and *Individual Assistance* (IA) for households. PA and IA may be authorized independently. Following a request by a Governor or Tribal Chief Executive, supported by joint Preliminary Damage Assessments, FEMA evaluates the evidence and the President designates the approved programs and areas. IA determinations weigh six factors—state fiscal capacity, uninsured household losses, population characteristics, community infrastructure impacts, casualties, and disaster-related unemployment—whereas PA determinations rely primarily on statewide per-capita cost indicators (updated annually), with qualitative flexibility for concentrated damage.

[4]Table A2 reports the timeline of all gubernatorial requests for federal disaster assistance that ultimately resulted in denial for the 29 cases used in the main analysis. The table shows that most of the decision lag in these denials arises from two sources: the delay between the disaster date and the governor's formal request for federal assistance, and the delay between the initial denial and the final decision following the appeal.

III. Empirical Methodology

To evaluate the economic effects of receiving federal assistance, we compare disasters approved for FEMA aid to those that were denied, conditional on similar initial severity. As demonstrated in the previous section, aid allocation is not random: denials are often associated with lower average economic impacts, partially explaining the outcome. However, a significant subset of denied disasters exceeded FEMA's official per capita impact threshold—the agency's primary eligibility criterion—yet still did not receive aid. These denials likely reflect non-economic factors, including political judgment, administrative discretion, intergovernmental coordination issues, insufficient documentation or incomplete damage assessments, variation in state-level lobbying or application quality, or strategic budgetary considerations at the federal level. As an illustration of a denied request, on October 6, 2008, Arizona Governor Janet A. Napolitano sought federal assistance for the Havasupai Tribe following flooding on Cataract Creek and the Havasupai Reservation during August 15–17, 2008. Because the request was sub-

Table 1—: Summary Statistics by FEMA program status

Panel A: State per capita impact ($)					
	N	Mean	SD	Min	Max
All disasters	493	4.49	6.38	0.06	67.81
Any program	435	4.66	6.26	0.32	67.81
Denials	58	3.21	7.17	0.06	43.44
PA only	373	4.33	5.04	0.32	63.65
Both PA and IA	62	6.66	10.91	1.24	67.81
Panel B: Lag in fiscal help (weeks)					
	N	Mean	SD	Min	Max
Any program	435	7.42	4.30	0	31
PA only	373	7.92	4.28	1	31
Both PA and IA	62	4.40	2.98	0	12
Denials	57	15.42	8.11	3.86	50.14
Panel C: Total help per capita ($)					
	N	Mean	SD	Min	Max
Any program	432	4.66	6.13	0.25	63.52
PA only	370	4.13	4.82	0.25	61.47
Both PA and IA	62	7.79	10.64	1.09	63.52

Note: Summary statistics are based on raw data covering the period 2006w1–2019w52. Panel A reports the state-level per capita economic impact (in USD) of natural disasters. Panel B presents the lag, in weeks, between disaster declaration and the receipt of fiscal assistance (for denials, the lag between disaster and denial decision). Panel C reports total public assistance per capita, combining Public Assistance (PA) and Individual Assistance (IA) programs. Denials in Panel B include the 57 cases (out of 58 reported in Panel A) for which we have valid information on denial dates; one case is excluded due to inconsistencies between the denial date and the disaster date. Panel C ("PA only") reports 370 of the 373 cases in Panel B for which we have valid information on public assistance per capita; three cases lack data on total public assistance and are therefore excluded from Panel C.

mitted after the 30-day regulatory deadline and no extension had been requested, it was denied for failing to meet the procedural requirements of 44 C.F.R. 206.36. Table B4 in the Appendix summarizes narrative evidence on bureaucratic and administrative factors underlying denial decisions.

Our identification strategy exploits quasi-random variation in federal aid allocation among disasters with similar observable initial severity.[5] This approach allows us to interpret the receipt of FEMA assistance as a policy intervention rather than a deterministic function of disaster impact. By comparing disasters that were equally severe on observable metrics—some of which received aid and others that did not—we isolate variation in aid decisions that is plausibly orthogonal to the disaster's initial damage. This assumption is crucial for estimating the marginal effect of federal assistance on economic recovery and for drawing credible causal inferences for the role of disaster aid.

To this end, we first exclude the mildest events from the group of denied disasters — where low-severity cases are more common — by removing those with an estimated state-level per capita impact below the FEMA's eligibility threshold. By definition, these disasters are denied assistance because they are relatively minor. By excluding these clear denial cases, we retain only denied assistance for disasters that are similar in severity to approved ones, enhancing the validity of our empirical approach. Table A1 in the Appendix shows that, after excluding disasters that did not meet FEMA's threshold, the two groups exhibit nearly identical average initial impacts—supporting the use of this quasi-experimental variation to estimate the effect of receiving federal assistance.

We further support our identification strategy by combining data on the party affiliation of state governors and U.S. presidents with information on whether disaster requests received federal assistance. Consistent with Schneider and Kunze (2025), who document political bias in federal disaster decisions for medium-sized events, we find that political alignment between the governor and president increases the likelihood of approval by about 6 percentage points (Appendix Table B3).[6] This pattern accords with political influences in disaster relief documented also by Garrett and Sobel (2003). Moreover, the illustrative narratives of denied declarations in Table B4 emphasize administrative delays or errors in denial decisions, thereby offering another narrative explanation for why some disasters that otherwise appear comparable to those receiving federal assistance are nonetheless denied.

Appendix D documents institutional features of the approval process that can

[5] Figure A2 shows that denied disasters are concentrated in the Northeast, Central, and Southern states, both in total denials (Panel A) and in the share of requests denied (Panel B), while the overall geographic distribution of disaster declarations exhibits no clear systematic pattern.

[6] To ensure comparability with Schneider and Kunze (2025), we restrict the sample to medium-sized disasters by keeping observations within the interquartile range of per-capita impacts. They show that after medium-intensity hurricanes, areas governed by the president's co-partisans receive up to twice as many disaster declarations, with political bias accounting for about 8 percent of total relief spending. Differences in our results may reflect their focus on hurricane declarations, whereas our sample spans a shorter period and covers a broader set of disaster types.

affect outcomes independently of measured disaster severity. In particular, the *Federal Emergency Management Agency (FEMA)*'s 30-day filing deadline and compliance with procedural requirements can generate denials even when underlying damages are similar, creating variation in federal assistance that is not mechanically tied to initial economic harm.

More importantly, Table B2 shows that federal disaster assistance is not systematically related to states' pre disaster economic conditions or fiscal capacity, including budget rules, rainy day funds, revenues, expenditures, debt, or property insurance coverage, consistent with U.S. Government Accountability Office (2012). This absence of systematic relationships lends support to our identifying assumption that, conditional on initial damages, residual variation in federal assistance is orthogonal to pre-disaster economic fundamentals.

We analyze how economic activity responds to a natural disaster depending on whether the disaster received fiscal assistance from FEMA, by estimating the following local projections (Jordá, 2005):

$$
\begin{aligned}
ECI_{i,t+h} = {} & \alpha_{i,h} + \beta_h \cdot \text{Impact}_{i,t} + \theta_h \cdot \left(\text{Impact}_{i,t} \times 1\{\text{AnyProgram}_{i,t} = 1\}\right) \\
& + \Psi_h^\top X_{i,t-1} + \sum_{l=1}^{8} \Gamma_{h,l} \cdot ECI_{i,t-l} + \sum_{l=1}^{8} \Phi_{h,l} \cdot \text{Natural Disaster}_{i,t-l} \\
& + \lambda_t + \varepsilon_{i,t+h}.
\end{aligned} \tag{1}
$$

Our outcome variable is the Weekly Economic Activity Index (ECI) for state i at horizon $t+h$, where h ranges from 0 to 52, allowing us to track the impact of disasters up to one year after the shock. The main regressor is $\text{Impact}_{i,t}$, a continuous variable measuring the estimated per capita economic cost of the disaster in dollars. To test whether fiscal aid mitigates these effects, we interact $\text{Impact}_{i,t}$ with an indicator variable $1\{\text{AnyProgram}_{i,t} = 1\}$, which equals one if the disaster received any form of official fiscal assistance. The coefficient β_h thus captures the average response of economic activity to a \$1 increase in disaster-related per capita losses for disasters that qualify for—but do not receive—fiscal assistance. The average effect for disasters that receive assistance is therefore given by $\beta_h + \theta_h$. The vector of controls $X_{i,t-1}$ includes lagged values of key fiscal variables—state revenue, expenditure, debt, and rainy day fund balances—as well as the share of the population with property insurance.[7]

We control for pre-disaster local economic conditions by including lags of ECI.

[7]Recent cross-country evidence shows that insurance mitigates the economic effects of natural disasters (Von Peter et al., 2024). Accordingly, our baseline specification controls for state-level property insurance coverage, though standard homeowners' policies typically exclude floods, making this an imperfect proxy for flood protection. Moreover, existing evidence suggests that expectations of federal aid may reduce flood insurance take-up (Browne and Hoyt, 2000; Landry et al., 2021) and that post-disaster assistance can affect participation in the National Flood Insurance Program (Bhattacharyya et al., 2024). Appendix B shows that our results are unchanged when excluding floods or controlling for total National Flood Insurance Program claims.

We also account for disaster persistence through lagged indicators of natural disaster exposure Natural Disaster$_{i,t-l}$, and include week-of-year fixed effects λ_t to absorb any residual seasonal variation in economic activity.[8] As highlighted in the previous section, we restrict the comparison to disasters with similar initial impacts. This design ensures that any observed differences in post-disaster outcomes can be attributed to the presence or absence of federal assistance, rather than to variation in initial disaster severity.

IV. Results

A. Any Program vs Denial

The results of our baseline specification, shown in Figure 1, reveal stark differences in post-disaster economic dynamics depending on the presence of federal aid. The figure illustrates the weekly responses of economic activity up to 52 weeks after a disaster. Solid blue lines depict outcomes for disasters that received any form of FEMA assistance, while dashed red lines represent those for which aid was denied and their corresponding 68% and 90% confidence bands.

In states where federal aid is denied, aggregate economic activity initially tracks its non-disaster average but then declines sharply and persistently, with the break occurring around 15 weeks after the event. This pattern broadly reflects the responses of weekly initial unemployment claims that display an abrupt and pronounced increase at the 15-week mark, driving most of the decline in the aggregate index, as illustrated in Figure B1 of the Appendix[9]. Table 1 shows that the average lag between a disaster and a denial decision is approximately 15 weeks. During this period, uncertainty about eligibility for federal assistance may delay workers' benefit filings; once a denial becomes clear, claims rise sharply. By contrast, in states receiving FEMA support, unemployment claims respond more smoothly and economic activity begins to recover about eight weeks after the disaster, remaining above the non-disaster average over the 52-week horizon.

These findings indicate that while the adverse effects of disasters are short-lived when federal aid is provided, the absence of assistance results in persistent economic costs—equivalent to a sustained 0.25 percentage points decline in growth relative to the non-disaster average. Fernández-Gallardo (2025), using a longer sample, finds that unconditionally disaster-induced losses average 0.1 percentage points one month after the event, but dissipate over time. Consistent with this, we find that in our sample the average impact of disasters is also transitory, albeit slightly smaller due to sample selection, with a peak decline in economic activity of approximately 0.07 percentage points occurring three weeks after the shock

[8]Our main results are robust to (i) controlling for past hazard-mitigation funds and (ii) allowing the week-of-year fixed effects to vary by state (λ_{it}), as shown in the Appendix.

[9]Figure B2 in the Appendix shows that economic activity measured by real GDP falls significantly on impact following the shock in states that were denied assistance, providing additional evidence of potential hysteresis in employment dynamics.

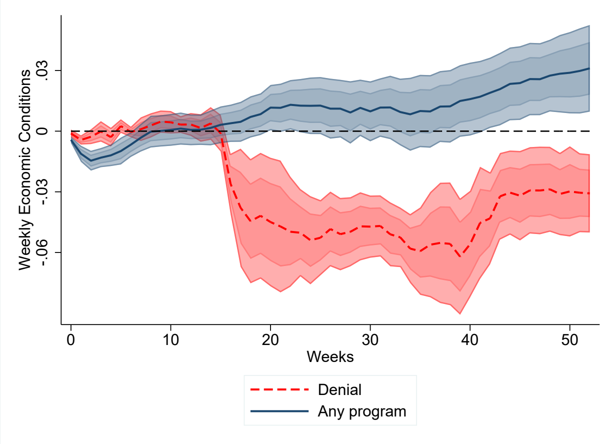


Figure 1. : Dynamic Response of Economic Activity to a Natural Disaster: Denial vs Any Fiscal Help

Notes: Estimated changes in the Weekly Economic Conditions Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 1, 2, \ldots, 52$, following a natural disaster, depending on whether the disaster received fiscal assistance from FEMA. The sample period is 2006w1–2019w52. The shaded area denotes the 68% and 90% confidence intervals, based on state-level clustered standard errors.

(see Figure B3 in the Appendix).[10]

We conduct two complementary robustness exercises to corroborate the baseline results. First, using aggregate quarterly data, Figure B2 reports local projections with real GDP as the outcome. Although the results are not directly comparable, since the ECI is measured in growth rates and real GDP in levels and because time aggregation may matter, the real GDP estimates confirm the baseline findings. Real GDP declines substantially following disasters without federal aid starting in the contemporaneous quarter, reaching a cumulative peak effect of about -0.3% after four quarters; in contrast, disasters that receive federal assistance display a much smaller contemporaneous output decline and return to the pre-disaster real GDP level within two to three quarters.

Second, although we do not have a sufficient number of observations to conduct a comprehensive regression discontinuity design (RDD) analysis, Table E1 presents results from a dynamic fuzzy RDD. This design exploits the FEMA impact threshold as an instrument for program approval and traces the effects of receiving federal assistance, relative to denial, on weekly economic conditions

[10]Figure 1 reports impulse responses scaled per dollar of per-capita disaster damage. To obtain the effects reported in the main text, we multiply these coefficients by the average damage in each sample. For denied disasters, average direct damage is approximately \$4.18 per capita (Panel A of Table A1). At $h = 20$ weeks, the estimated coefficient is $\hat{\beta}_{20} \approx 0.06$ percentage points per \$1 of per-capita damage, yielding $0.06 \times 4.18 \approx 0.25$ percentage points loss in weekly economic activity for the average denied disaster. Figure B3 applies the same scaling for *all* disasters, for which average per-capita damage is \$4.21. The maximum impact occurs at $h = 3$ weeks with $\hat{\beta}_3 \approx 0.015$ per dollar, corresponding to a peak decline of $0.015 \times 4.21 \approx 0.06$–$0.07$ percentage points in economic activity.

from the disaster week up to one year after the event. The estimated RDD effects are positive at all horizons and economically meaningful. Confirming our baseline estimates, they are most precisely estimated at intermediate horizons of 20–35 weeks. Moreover, the effect on average economic activity over the first 53 weeks is positive and marginally significant, reinforcing the conclusion that federal assistance mitigates and gradually reverses the adverse economic effects of disasters.

Importantly, our focus on disasters of comparable initial severity highlights the critical role of federal assistance in shaping recovery trajectories. The denial of aid leads to significantly larger and more persistent economic losses, reinforcing the importance of federal support in promoting post-disaster resilience.

B. Heterogeneity in Fiscal Assistance and Disaster Recovery

We investigate how key features of FEMA's fiscal assistance shape the dynamic responses to natural disasters. Specifically, we examine three dimensions of heterogeneity in aid delivery: *timing*, *program composition*, and *amount*.

First, we analyze the *timing* of disbursement by comparing disasters where aid was delivered within the same week or the following week of the disaster declaration to those where assistance was delayed by two weeks or more. Second, we consider *program composition*, contrasting disasters that received only Public Assistance (PA) with those that also received Individual Assistance (IA). Third, we assess the *scale* of aid by classifying disasters according to whether per capita disbursements (PA) exceeded the historical median among all public assistance aid–receiving events.

A key empirical challenge arises from the fact that these aid characteristics are not randomly assigned. As documented in Table 1 (Section II), disasters with higher initial severity are systematically more likely to receive prompt aid, qualify for both PA and IA, and obtain larger funding amounts.

Nevertheless, substantial within-group heterogeneity persists among disasters that received aid. This variation permits comparisons across events with similar initial economic impacts but differing aid configurations, such as, contrasting cases with timely versus delayed disbursements, substantial versus modest total assistance, and those that included individual transfers (IA) versus those limited to public infrastructure support (PA) alone.

To ensure comparability across groups, we restrict our analysis to exclude the lower tail of the severity distribution in cases where lower group averages are driven by very mild events. This restriction sharpens identification by focusing on disasters of comparable initial economic costs, allowing us to exploit quasi-random variation in the timing, composition, and magnitude of aid. We thereby provide credible estimates of how specific features of fiscal assistance influence post-disaster recovery trajectories.

Table A1 in the Appendix outlines the specific sample restrictions we apply and presents, alongside these, the mean economic cost of disasters prior to the restriction and the number of disasters. The table shows that, after these adjustments, disasters across different aid categories exhibit comparable initial severity. For example, when no sample restrictions are applied, disasters that received aid in week 0 or 1 typically had higher average initial severity than those receiving aid in week 2 or later—a pattern that reflects the tendency for less severe disasters to experience delays in federal response. However, we also observe that many disasters with comparable initial economic impacts received aid only after a delay of more than two weeks. To correct for this imbalance, we exclude the bottom 10th percentile of disasters—ranked by state-level per capita impact—from the group receiving aid in week 2 or later. This likely removes disasters whose delayed fiscal assistance was due to their relatively low initial impact. After applying this restriction, both groups exhibit nearly identical average severity, allowing us to isolate variation in the timing of aid that is not mechanically driven by disaster magnitude.

We apply a similar approach to the other two dimensions of aid heterogeneity. When comparing disasters that received only Public Assistance (PA) to those that received both PA and Individual Assistance (IA), we exclude the mildest disasters from the PA-only group to ensure comparability. In contrast, when comparing disasters that received above- versus below-median per capita aid, simply excluding very mild disasters from the lower-aid group would not yield comparable samples, because most disasters receiving above- and below-median aid differ systematically in initial economic damages. For this analysis, we therefore focus on a subset of more comparable disasters by restricting the sample to the largest disasters in the below-median total aid group and the mildest disasters in the above-median total aid group. The specific restriction is reported in Table A1. These adjustments allow us to focus on variation in aid composition and scale that is not confounded by underlying differences in disaster severity, thereby improving the credibility of our identification strategy.

We estimate separate regressions based on the following local projection specification, with each regression corresponding to one dimension of heterogeneity described above:

$$
\begin{aligned}
ECI_{i,t+h} = {} & \alpha_{i,h} + \beta_h \cdot \text{Impact}_{i,t} + \theta_h \cdot \big(\text{Impact}_{i,t} \times 1\{\text{Fiscal Generosity}_{i,t} = 1\}\big) \\
& + \Psi_h^{\top} X_{i,t-1} + \sum_{l=1}^{8} \Gamma_{h,l} \cdot ECI_{i,t-l} + \sum_{l=1}^{8} \Phi_{h,l} \cdot \text{Natural Disaster}_{i,t-l} \\
& + \eta_h \cdot 1\{\text{Denial}_{i,t} = 1\} + \lambda_t + \varepsilon_{i,t+h} \qquad (2)
\end{aligned}
$$

Our outcome variable is the Weekly Economic Conditions Index (ECI) in state i at horizon $t+h$. The main regressor is $\text{Impact}_{i,t}$, a continuous variable measuring the realized per capita cost of a natural disaster in dollars, conditional on the disaster having received federal assistance.

To study heterogeneity in the effects of federal assistance, we estimate regressions that interact $\text{Impact}_{i,t}$ with an indicator $1\{\text{Fiscal Generosity}_{i,t} = 1\}$, defined along three dimensions. For *timing*, the indicator equals one if aid is delivered within two weeks of the disaster declaration. For *aid composition*, it equals one if the disaster receives both Public Assistance (PA) and Individual Assistance (IA), and zero if it receives only PA. For *aid amount*, it equals one if per capita Public Assistance exceeds the historical median among aid-receiving disasters. All other covariates follow the baseline specification, and standard errors are clustered at the state level.[11]

The coefficient β_h captures the average dynamic effect of a \$1 increase in disaster-related damages under the baseline condition in which $\text{Fiscal Generosity}_{i,t} = 0$ (i.e., slow aid, only PA, or below-median aid). The coefficient θ_h captures the differential effect when $\text{Fiscal Generosity}_{i,t} = 1$, reflecting how the response to disaster intensity varies with the timing, composition, or amount of assistance received.

Figure 2 summarizes the dynamic effects of federal aid characteristics on post-disaster economic activity. Panel (a) compares disasters receiving immediate aid (solid blue line) with those facing delays exceeding two weeks (dashed red line), with 68% and 90% confidence bands. While both groups begin to recover about two months after the disaster, immediate aid is associated with significantly stronger and more persistent growth over the subsequent year.[12]

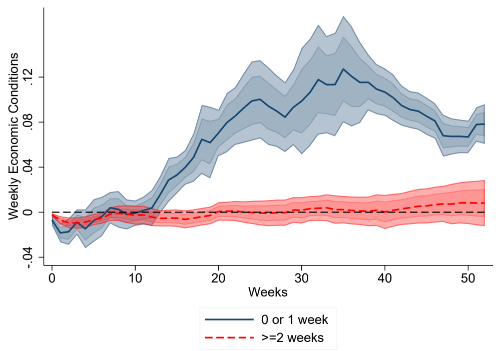
Panel (b) examines aid composition. Disasters receiving both PA and IA experience smaller short-run losses and larger long-run gains than those receiving only PA, though the estimates are statistically significant only at the 10 percent level in the short run. Panel (c) focuses on aid magnitude. States receiving above-median per capita assistance exhibit little immediate contraction and outperform the non-disaster historical average one year after the event, while those receiving below-median aid recover more slowly and remain well below trend. Overall, the results show that the quality of federal disaster assistance matters. Timely delivery, broader program coverage, and higher per capita disbursements are all associated with faster and more persistent post-disaster recovery, underscoring the importance of adequately funded and well-targeted federal relief.

C. *The Role of Rainy Day Funds and Balanced Budget Rules*

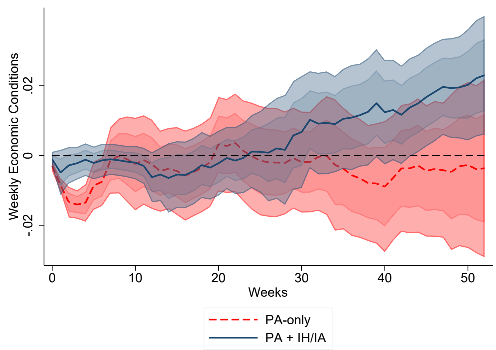
We next examine how post-disaster economic responses vary with states' ex ante fiscal capacity and institutional constraints, focusing on disasters that received

[11] Since $\text{Impact}_{i,t}$ is positive only for disasters receiving aid, we additionally control for aid denial using an indicator for disasters that requested but did not receive federal assistance.

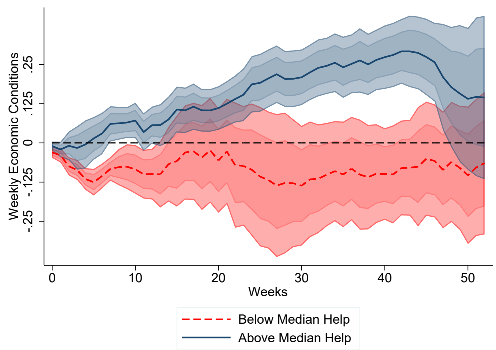
[12] These results warrant caution given the small number of disasters receiving assistance within two weeks. Also, although average initial costs are similar, the largest disaster among those with assistance lags longer than two weeks is costlier than the largest disaster with shorter lags (Table A1). Appendix Figure B5 addresses this by splitting longer lags into 4–12 weeks and more than 12 weeks. For the latter, the largest-cost disaster is about \$14 per capita, below the \$18.56 per capita for disasters receiving aid within two weeks. Even so, longer lags are associated with deeper and more persistent economic losses, confirming that delayed assistance worsens outcomes.



(a) By Lag in Fiscal Help



(b) By Program Status



(c) By Total Help

Figure 2. : Dynamic Response of Economic Activity to a Natural Disaster: Heterogeneity in Fiscal Help

Notes: Estimated cumulative changes in the Weekly Economic Conditions Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 1, 2, \ldots, 52$, following a natural disaster. The figure explores heterogeneity in responses depending on the type of program (e.g., Public Assistance only vs. both PA and IA), the lag in fiscal assistance, and the total amount per capita (\$) of fiscal help received. The sample period is 2006w1–2019w52. The shaded area denotes the 68% and 90% confidence intervals, based on state-level clustered standard errors.

federal aid.[13] We consider two dimensions of fiscal preparedness: *rainy day fund availability*, comparing states with above- versus below-median balances before the event, and *budget rule strength*, comparing states with and without strong balanced budget requirements. A key concern is that fiscal characteristics may correlate with initial disaster severity. To ensure comparability, we restrict the sample by excluding the mildest disasters from groups with lower average severity, aligning the distribution of initial impacts across groups. For instance, because disasters in states without strong balanced budget rules are less severe on average, we exclude the bottom 20th percentile of events by per capita impact from that group. We apply the same approach when comparing states with above- and below-median rainy day fund balances, isolating the role of fiscal and institutional capacity in shaping recovery outcomes.[14]

We estimate a series of local projection regressions to examine how pre-disaster fiscal conditions shape the dynamic response to economic shocks. In contrast to the previous section—where we interacted the per capita disaster impact with an indicator for fiscal generosity—we now interact $\text{Impact}_{i,t}$ with an indicator variable $1\{\text{Fiscal Preparedness}_{i,t} = 1\}$, reflecting the fiscal environment prior to the disaster, specifically measured at time $t-1$.

To capture heterogeneity across fiscal dimensions, we consider two alternative definitions of $1\{\text{Fiscal Preparedness}_{i,t} = 1\}$. First, the indicator equals one if the state's rainy day fund—measured in the week before the disaster—was above the cross-sectional median. Second, it equals one if the state lacked a strong balanced budget rule at that time. We estimate separate regressions for each definition.

The coefficient θ_h captures the differential effect of disaster intensity for states with either greater ex-ante fiscal capacity - measured by rainy day funds, or looser fiscal constraints. All remaining controls—including lagged economic indicators, fiscal variables, past disaster exposure, and seasonal fixed effects — are defined as in the baseline specification. Standard errors are clustered at the state level.

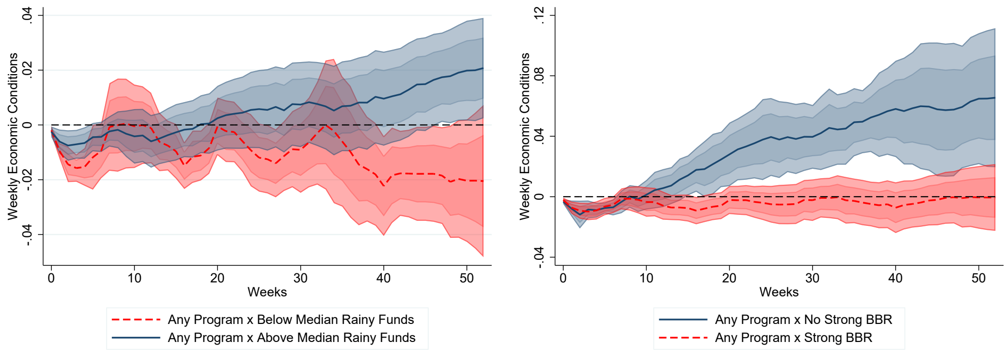
Figure 3 presents the results.[15] Panel (a) shows that states with above-median rainy day fund balances recover more quickly following a disaster. On average, these states return to pre-disaster economic activity levels within 10 weeks (solid blue line) and outperform the historical non-disaster average by week 40. In contrast, states with below-median rainy day funds experience a substantially slower recovery and remain below the historical average even one year after the shock (dashed red line).

In contrast, the presence of strict budgetary requirements appears to have little effect on recovery over the first 10 weeks following a disaster. However, beyond that horizon, states with looser budget rules begin to significantly outperform

[13] The small number of denials precludes credible heterogeneity analysis by state fiscal characteristics.

[14] Table A1 in the Appendix summarizes the sample restrictions ensuring comparability across observations. Additional details on the construction of fiscal measures are provided in the Appendix.

[15] These results are based on all disasters that receive any type of federal assistance. Figure B7 in the Appendix shows that the findings are robust when we re-estimate these two models using only disasters that receive public assistance but not individual assistance.



(a) Any Program and Pre-Disaster Rainy Day Funds (b) Any Program and Pre-Disaster Balanced Budget Rules

Figure 3. : Dynamic Response of Economic Activity to a Natural Disaster: Heterogeneity in Fiscal Preparedness

Notes: Estimated cumulative changes in the Weekly Economic Conditions Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 1, 2, \ldots, 52$, following a natural disaster. The sample period is 2006w1–2019w52. The shaded area denotes the 68% and 90% confidence intervals, based on state-level clustered standard errors. Estimates are shown separately depending on whether the affected state had a rainy day fund above or below the cross-sectional median, and whether it had a strong budget balance rule in place during the week prior to the disaster.

those with stricter constraints.

These results suggest that strong ex-ante fiscal capacity — particularly in the form of well -funded rainy day reserves — enhances state-level resilience to disasters by enabling faster and more sustained recoveries. In contrast, strict balanced budget rules appear to constrain recovery over longer horizons, potentially by limiting fiscal flexibility in the aftermath of shocks. Our findings align with Grosse-Steffen et al. (2025) and Costa and Hooley (2025): fiscal space plays a central role in effectively reducing the adverse consequences of disasters. Policymakers should therefore consider both the adequacy of fiscal buffers and the flexibility of budgetary rules when designing frameworks aimed at improving disaster preparedness and economic resilience.

D. Hazard Mitigation Programs and Natural Disaster Probability

In addition to PA and IA, FEMA administers the Hazard Mitigation Assistance (HMA) program, which provides funding to state, local, tribal, and territorial governments to reduce vulnerability to future disasters. The program seeks to break the cycle of damage and reconstruction through targeted mitigation planning and projects. Given the rising frequency and severity of disasters, evaluating the effectiveness of such mitigation efforts is essential. FEMA data offer a valuable opportunity to empirically assess whether these programs achieve their intended goals.

To assess the effectiveness of hazard mitigation programs, we estimate the following linear model:

$$\text{NaturalDisaster}_{i,t+h} = \alpha_{i,h} + \beta_h \cdot 1\{\text{HazardProgram}_{i,t} = 1\} + \sum_{l=1}^{8} \Gamma_{h,l} \cdot ECI_{i,t-l}$$

$$+ \sum_{l=1}^{8} \Psi_{h,l} \cdot \text{NaturalDisaster}_{i,t-l} + \varepsilon_{i,t+h} \tag{3}$$

The dependent variable, $\text{NaturalDisaster}_{i,t+h}$, is an indicator equal to one if a storm or flood triggering FEMA assistance occurs in state i at horizon $t + h$, and zero otherwise. The key explanatory variable is $1\{\text{HazardProgram}_{i,t} = 1\}$, which equals one if a FEMA hazard mitigation project was implemented in state i during quarter t. The model includes state fixed effects $\alpha_{i,h}$ to control for time-invariant differences in baseline disaster risk. We control for local economic conditions using eight lags of the Weekly Economic Conditions Index (ECI) and for persistence in disaster exposure through eight lags of $\text{NaturalDisaster}_{i,t-l}$. The coefficient β_h captures the effect of hazard mitigation on the likelihood of a future FEMA-designated disaster at horizon h. Standard errors are clustered at the state level to account for serial correlation in the error term $\varepsilon_{i,t+h}$.[16]

Because hazard mitigation programs reduce risk only gradually, we estimate their effects over long horizons—up to 40 quarters (10 years) after implementation—and report probabilities starting at $h = 8$ (two years post-implementation). The sample spans 1987—2024. Unlike earlier analyses, this specification does not require per capita damage measures, only the occurrence of a qualifying disaster, allowing us to extend the sample back to 1987.[17]

The unconditional quarterly probability of a FEMA-recognized storm or flood is about 20 percent. Figure 4 shows that hazard mitigation programs reduce this probability by roughly 4 percentage points in the long run, with statistically significant effects emerging about seven years after implementation. Short-run effects are limited, but the long-run impact is sizable, underscoring the role of mitigation in reducing future disaster risk.

V. Conclusions

Natural disasters generate large and recurring economic losses, yet evidence on the effectiveness of disaster-related fiscal policy remains limited. This paper contributes by assembling a novel dataset that links FEMA disaster declarations

[16]Because FEMA declarations are typically sought for incidents that overwhelm state and local capacity, a reduction in the likelihood of a FEMA-assisted disaster is interpreted as a reduction in the occurrence of disasters causing substantial destruction—consistent with hazard mitigation lowering the incidence of severe events.

[17]Starting the sample in 2006, as in previous sections, would restrict inference at long horizons.

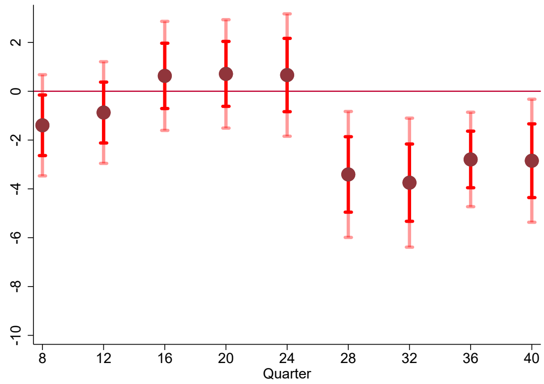


Figure 4. : Effect of a Hazard Mitigation Program on the Probability of Disasters Requiring Federal Assistance

Notes: Estimated change in the probability that a storm or flood results in a disaster requiring assistance from FEMA, following the implementation of a state-level hazard mitigation program. The outcome is a binary indicator equal to one if a disaster requiring federal assistance occurs at horizon $h = 8, 12, \ldots, 40$, where h is measured in quarters after program implementation. The solid bars denote the 68% and 90% confidence intervals., based on state-level clustered standard errors.

with detailed information from Preliminary Damage Assessments. Exploiting quasi-random variation among disasters of similar severity that did or did not receive federal assistance, we estimate the marginal effects of aid on recovery using local projections.

Federal assistance makes a significant difference for economic recovery. In states where aid is denied, aggregate economic activity declines markedly and persistently.

Our findings underscore the importance of both ex ante fiscal preparedness and ex post federal intervention. States with stronger fiscal capacity, proxied by above median rainy day funds, recover faster and more durably, whereas strict balanced budget rules appear to constrain longer run recovery. Timely, comprehensive, and generous federal aid accelerates recovery and generates persistent gains, with prompt disbursement, broad program coverage, and higher per capita allocations linked to better outcomes. We also show that hazard mitigation programs, despite limited short run effects, durably reduce the likelihood of future disasters recognized by the Federal Emergency Management Agency.

Taken together, these results underscore the need for a coordinated and forward looking disaster policy framework. Building fiscal buffers, preserving budgetary flexibility, ensuring the rapid and adequate deployment of federal aid, and investing in long term mitigation can jointly strengthen economic resilience in the face of rising climate related risks. Our framework offers a scalable and policy relevant approach for evaluating fiscal responses to natural disasters in the United States and beyond.

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A1. ECI index

The state-level Economic Conditions Index (ECI) is scaled to align with the average four-quarter growth rate of U.S. real GDP, allowing for a nationally consistent interpretation of state-level performance. The index serves as a real-time indicator of whether economic conditions in a given state deviate from the national historical trend. A value of zero indicates economic conditions consistent with the long-run year-on-year growth rate of U.S. real GDP. Figure A1 presents the time-series evolution of the ECI across U.S. states, showing the 5th, median, and 95th percentiles. The figure demonstrates that the ECI effectively captures state-level economic fluctuations over the sample period.

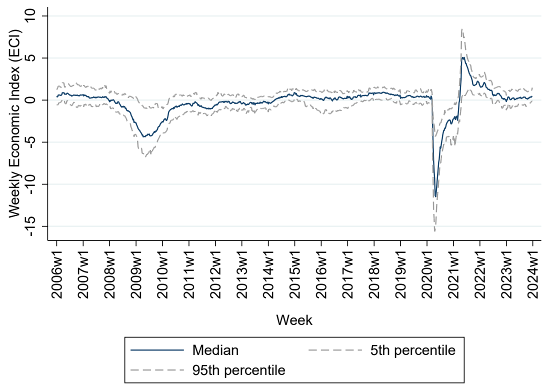
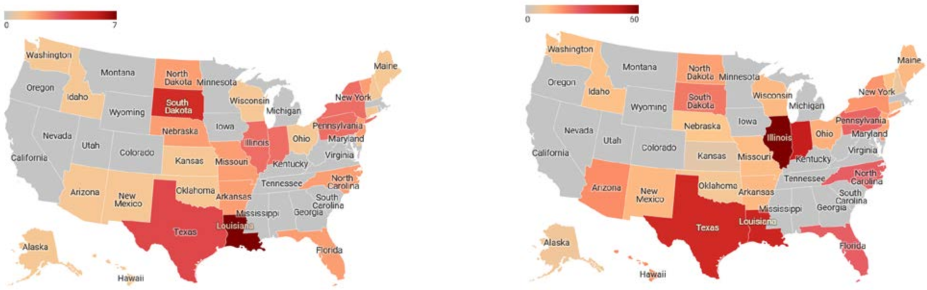


Figure A1. : Weekly Economic Conditions Index (ECI)

Notes: The figure presents the time series of the state-level Weekly Economic Conditions Index (ECI) from Baumeister et al. (2024). Each week, we calculate the median ECI across states, along with the 5th and 95th percentiles. The sample period spans from 2006w1 to 2023w52.



(a) Total number of disasters that were denied federal assistance

(b) % of disasters that were denied federal assistance

Figure A2. : Number and share of disasters that were denied federal assistance, by U.S. state.

Notes: This figure shows the geographical distribution, by U.S. state, of disasters that were denied federal assistance. Panel (a) shows the total number of disasters that were denied federal assistance conditional on requesting assistance. Panel (b) shows the proportion of disasters that were denied federal assistance conditional on requesting assistance. Sample 2006w1–2019w52.

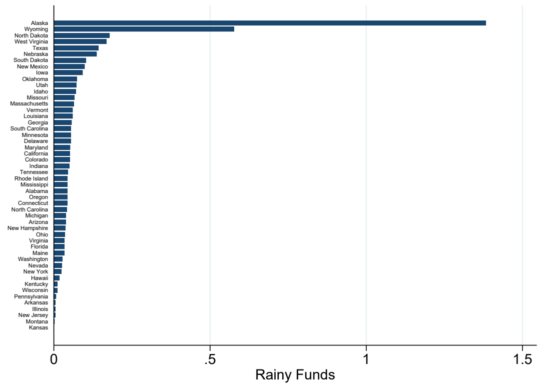


Figure A3. : Average Rainy Day Funds by State as a share of general expenditures

Notes: The figure shows the average rainy day funds across U.S. states over time. Values are expressed as a share of state general fund expenditures. The sample period spans from 2006 to 2019.

Table A1—: Disaster Impact by FEMA Program Status and State-Level Fiscal Characteristics

Panel A: Denial vs Any Program

	Mean	SD	Min	Max	N	PR Mean	PR N
Any Program	4.21	3.97	0.32	29.78	431	4.66	435
Denial	4.18	6.29	1.33	31.77	29	3.21	58
Total	4.21	4.15	0.32	31.77	460	4.49	493

Disaster Sample Restrictions: (i) Denials must exceed FEMA's per capita impact threshold; (ii) exclude disasters above the 99th percentile within each group.

Panel B: By Lag in Fiscal Help

	Mean	SD	Min	Max	N	PR Mean	PR N
$<$ 2 weeks	4.95	4.83	1.53	18.56	12	4.95	12
$\geq$ 2 weeks	5.05	6.56	1.53	67.81	377	4.65	423
Total	5.05	6.51	1.53	67.81	389	4.66	435

Disaster Sample Restrictions: (i) Exclude disasters below the 10th percentile for the group with fiscal lag $\geq$ 2 weeks.

Panel C: Public Assistance vs Both PA and IA

	Mean	SD	Min	Max	N	PR Mean	PR N
Public Assistance (PA) Only	6.65	6.19	2.68	63.65	191	4.33	373
PA + Individual Assistance (IA)	6.66	10.91	1.24	67.81	62	6.66	62
Total	6.65	7.60	1.24	67.81	253	4.66	435

Disaster Sample Restrictions: (i) Exclude disasters below the 50th percentile for the PA-only group.

Panel D: Above vs Below Median Public Assistance Help

	Mean	SD	Min	Max	N	PR Mean	PR N
Above Median PA Help	2.78	0.12	2.53	2.93	18	6.68	188
Below Median PA Help	2.74	0.26	2.59	3.44	10	1.90	182
Total	2.77	0.18	2.53	3.44	28	4.13	370

Disaster Sample Restrictions: (i) Exclude all but top 5% of disasters in the below-median group; (ii) exclude all but bottom 10% in the above-median group.

Panel E: Any Program and Rainy Funds

	Mean	SD	Min	Max	N	PR Mean	PR N
Rainy Fund Above Median	5.46	6.88	1.24	67.81	240	5.46	240
Rainy Fund Below Median	5.49	6.89	2.53	63.65	99	3.68	195
Total	5.47	6.87	1.24	67.81	339	4.66	435

Disaster Sample Restrictions: (i) Exclude disasters below the 50th percentile for the group with rainy funds below the median.

Panel F: Any Program and Budget Balanced Rules

	Mean	SD	Min	Max	N	PR Mean	PR N
BBR Strong	4.81	6.92	1.24	67.81	321	4.81	321
BBR Not Strong	4.93	3.97	1.84	21.46	91	4.24	114
Total	4.84	6.38	1.24	67.81	412	4.66	435

Disaster Sample Restrictions: (i) Exclude disasters below the 20th percentile for the group without strong BBR.

Note: Each panel reports the average state-level per capita impact (in USD) of disasters in the effective sample used for the results presented in Section IV. Sample restrictions are applied to ensure that initial severity is comparable across groups. "PR Mean" and "PR N" refer to the average state-level per capita impact and number of disasters in each group before any sample restrictions are applied.

Table A2—: Denials Timeline by Disaster

Disaster Type	State	Date of Disaster	Gov. Request Date	First Denial Date	Final Denial Date	Lag Dis.–Gov. (weeks)	Lag Gov.–First (weeks)	Lag First–Final (weeks)	Lag Dis.–Final (weeks)	Main lag
Storm and Flooding	Alaska	11/27/2019	02/06/2020	03/05/2020	No appeal	10	4	No appeal	14	Disaster–Gov. request
Storm	Arkansas	10/21/2019	12/18/2019	01/24/2020	04/24/2020	8	5	13	26	First–Final denial
Storm	Florida	10/24/2012	11/01/2012	11/29/2012	01/17/2013	1	4	7	12	First–Final denial
Storm	Hawaii	08/07/2014	08/21/2014	08/28/2014	10/16/2014	2	1	7	10	First–Final denial
Storm	Idaho	12/22/2016	02/28/2017	03/21/2017	05/02/2017	10	3	6	19	Disaster–Gov. request
Storm	Indiana	01/31/2011	03/14/2011	04/20/2011	No appeal	6	5	No appeal	11	Disaster–Gov. request
Storm and Flooding	Indiana	06/07/2015	08/31/2015	09/09/2015	10/20/2015	12	1.5	6	20	Disaster–Gov. request
Storm and Flooding	Kansas	05/22/2016	07/21/2016	08/03/2016	09/29/2016	9	2	8	19	Disaster–Gov. request
Flooding	Louisiana	12/28/2015	03/02/2016	04/13/2016	06/15/2016	9	6	9	24	Disaster–Gov. request
Storm and Flooding	Missouri	06/04/2007	07/03/2007	08/03/2007	12/05/2007	4	4.5	18	27	First–Final denial
Storm and Flooding	Nebraska	08/18/2011	09/15/2011	09/30/2011	11/09/2011	4	2	6	12	First–Final denial
Storm and Flooding	New Hampshire	04/15/2014	05/21/2014	06/11/2014	07/17/2014	5	3	5	13	Disaster–Gov. request
Storm and Flooding	New Jersey	10/01/2015	10/29/2015	11/10/2015	12/21/2015	4	2	6	12	First–Final denial
Storm	New Mexico	12/26/2015	02/16/2016	03/09/2016	05/10/2016	7	3	9	19	First–Final denial
Storm and Flooding	New York	06/30/2017	08/31/2017	12/06/2017	01/26/2018	9	14	7	30	Gov. req.–First denial
Storm and Flooding	North Carolina	05/15/2018	07/30/2018	08/20/2018	11/09/2018	11	3	11.5	26	First–Final denial
Storm	North Carolina	09/25/2015	10/28/2015	11/06/2015	12/08/2015	4.5	1.5	4.5	11	Disaster–Gov. request
Storm	North Dakota	07/20/2017	08/24/2017	11/14/2017	No appeal	5	12	No appeal	17	Gov. req.–First denial
Storm and Flooding	North Dakota	08/15/2014	10/07/2014	10/23/2014	11/26/2014	7	2	5	14	Disaster–Gov. request
Storm and Flooding	Oklahoma	04/25/2009	05/21/2009	06/19/2009	09/02/2009	4	4	11	19	First–Final denial
Storm and Flooding	Pennsylvania	02/15/2018	06/22/2018	07/11/2018	10/15/2018	19	2.5	13.5	35	Disaster–Gov. request
Storm and Flooding	Pennsylvania	05/28/2009	06/29/2009	07/17/2009	09/03/2009	5	2.5	7	15	First–Final denial
Storm	South Dakota	05/17/2018	06/14/2018	08/31/2018	10/15/2018	4	11	6	21	Gov. req.–First denial
Storm and Flooding	South Dakota	06/13/2014	07/02/2014	07/10/2014	No appeal	3	1	No appeal	4	Disaster–Gov. request
Storm and Flooding	South Dakota	08/02/2019	09/10/2019	10/07/2019	11/22/2019	5.5	4	6.5	16	First–Final denial
Storm	South Dakota	06/29/2018	08/17/2018	09/18/2018	No appeal	7	4.5	No appeal	12	Disaster–Gov. request
Storm and Flooding	Vermont	07/28/2014	09/05/2014	09/23/2014	No appeal	5	2.5	No appeal	8	Disaster–Gov. request
Storm	Vermont	11/26/2018	01/04/2019	02/14/2019	04/08/2019	6	6	7	19	First–Final denial
Storm and Flooding	Wisconsin	07/11/2016	09/02/2016	09/16/2016	10/27/2016	8	2	6	16	Disaster–Gov. request

Note: This table reports the timeline of all gubernatorial requests for federal disaster assistance that ultimately received a denial for the 29 denials used in the main analysis. "Date of Disaster" is the onset date of the disaster event. "Gov. Request Date" is the date on which the governor formally requested a federal disaster declaration. "First Denial Date" is the date of FEMA's or the President's initial denial. "Final Denial Date" is the date of the final determination, incorporating any appeal; "No appeal" indicates that no appeal was filed after the first denial. "Lag Dis.–Gov." is weeks between the disaster date and the governor's request. "Lag Gov.–First" is weeks between the request and first denial. "Lag First–Final" is weeks between the first and final denial (conditional on an appeal). "Lag Dis.–Final" is weeks between the disaster date and the final denial. "Main lag" indicates which segment of the decision process accounts for the longest delay for that case.

Table A3—: Balanced Budget Rule (BBR) Classification by State

State	None	Statutory	Strong	Weak
Alabama			14	
Alaska		14		
Arizona	5	9		
Arkansas		2	12	
California			14	
Colorado		5	9	
Connecticut		5	9	
Delaware		14		
Florida		9	5	
Georgia			14	
Hawaii			14	
Idaho			14	
Illinois			14	
Indiana	12			2
Iowa		12	2	
Kansas			14	
Kentucky		2	12	
Louisiana		9	5	
Maine		5	9	
Maryland			14	
Massachusetts		14		
Michigan			14	
Minnesota		14		
Mississippi		5	9	
Missouri			14	
Montana			14	
Nebraska			14	
Nevada			14	
New Hampshire		5	7	2
New Jersey			14	
New Mexico			14	
New York			12	2
North Carolina		5	9	
North Dakota			14	
Ohio		5	9	
Oklahoma			14	
Oregon			14	
Pennsylvania			14	
Rhode Island			14	
South Carolina			14	
South Dakota			14	
Tennessee			14	
Texas			14	
Utah			14	
Vermont	12			2
Virginia			14	
Washington			5	9
West Virginia			14	
Wisconsin		5	9	
Wyoming			14	

Note: This table classifies U.S. states based on the strength of their Balanced Budget Rules (BBRs). Values indicate the number of years (from 2006 to 2019) that each state was in a given category. Categories are mutually exclusive by year and defined as follows: **None**, no BBR; **Weak**, rule exists but is easily bypassed or not enforced; **Statutory**, rule enforced by law but with limited enforcement; and **Strong**, legally binding and strictly enforced. Data are from Deng and Liu (2025).

Other Results

Table B1—: Dynamic Response of Initial Jobless Claims: Denial vs Any Program

	Horizon h				
	$h = 10$	$h = 20$	$h = 30$	$h = 40$	$h = 50$
Denial (%)	-0.834***	-0.587***	3.791**	3.742***	1.286
	(0.224)	(0.208)	(1.780)	(0.786)	(0.987)
Any program (%)	0.128	-0.035	-0.137	-0.091	-0.593**
	(0.142)	(0.272)	(0.219)	(0.276)	(0.286)

Note: Estimated percentage changes in weekly initial jobless claims from local projections at horizon h. *Denial* reports β_h, the effect per unit of disaster impact when no federal aid is granted. *Any program* reports $\beta_h + \theta_h$, the effect when federal aid is granted. The sample period spans from 2006w1 to 2019w52. Robust standard errors clustered by state in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B2—: Predicting Federal Disaster Assistance

	Any program at t
Strong balanced-budget requirement at $t-1$	0.114
	(0.072)
Rainy day funds at $t-1$	0.682
	(0.464)
Revenue at $t-1$	-0.000
	(0.000)
Expenditure at $t-1$	0.000
	(0.000)
Debt at $t-1$	0.000
	(0.000)
ECI at $t-1$	-0.117
	(0.101)
ECI at $t-2$	-0.029
	(0.112)
ECI at $t-3$	0.208
	(0.127)
ECI at $t-4$	-0.069
	(0.080)
Property insurance at $t-1$	1.161
	(1.976)
Observations	480
Joint test: all coefficients = 0 (p-value)	0.546

Note: This table reports coefficients from state fixed-effects linear probability models estimated at the state–week level. The sample is restricted to disaster weeks. The dependent variable equals one if a state receives federal disaster assistance through Public Assistance (PA), Individual Assistance (IA), or both in week t, and zero if assistance is denied. All predictors are measured in the week prior to the disaster, $t-1$. *Strong balanced-budget requirement at* $t-1$ is an indicator for whether the state is subject to a strong balanced-budget rule in $t-1$. *Rainy day funds at* $t-1$ measures the state's budget stabilization fund balance in $t-1$ as a share of general expenditures. *Revenue at* $t-1$, *Expenditure at* $t-1$, and *Debt at* $t-1$ are measured in dollars. *Property insurance at* $t-1$ measures the share of the population with property insurance in $t-1$. The Economic Conditions Index (ECI) is included at four separate weekly lags ($t-1$ through $t-4$). Observations refer to the number of disasters (state–week observations) in the regression sample. Standard errors, clustered by state, are in parentheses. The row "Joint test" reports the p-value from an F-test of the null that all reported coefficients equal zero. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B3—: Partisan Alignment and the Allocation of Federal Disaster Relief

	Denial at t	Any program at t
Same party alignment	-0.058*	0.058*
	(0.030)	(0.030)
p-value	[0.054]	[0.054]
Observations	251	251

Note: This table reports OLS estimates at the state–week level. The sample is restricted to disaster weeks and, following Schneider and Kunze (2025), further restricted to medium-size disasters by excluding observations with reported per-capita disaster impact below the 25th percentile or above the 75th percentile (retaining only disasters in the interquartile range of per-capita impact). The key regressor, *Same party alignment*, equals one if the state governor and the U.S. president are from the same political party at the time of the disaster and zero otherwise. The dependent variable in column 1, *Denial at t*, equals one if federal disaster assistance is denied in state–week t and zero if assistance is approved. The dependent variable in column 2, *Any program at t*, equals one if the state receives federal disaster assistance through Public Assistance (PA), Individual Assistance (IA), or both in state–week t and zero if assistance is denied. Observations refer to the number of disasters (state–week observations) in the regression sample. Standard errors are heteroskedasticity-robust and reported in parentheses; p-values are reported in brackets. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

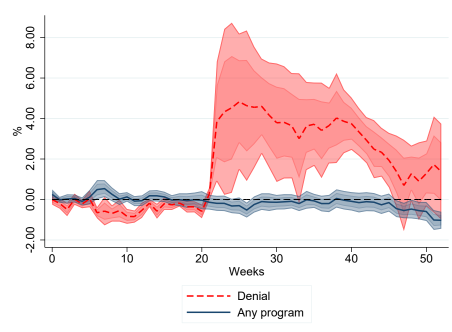


Figure B1. : Dynamic Responses to a Natural Disaster: Denial vs Any Fiscal Help

Notes: Estimated changes in weekly initial jobless claims at horizons $h = 0, 1, 2, \ldots, 52$, following a natural disaster, depending on whether the disaster received fiscal assistance from FEMA. The sample period is 2006w1–2019w52. The shaded area denotes the 68% and 90% confidence intervals, based on state-level clustered standard errors.

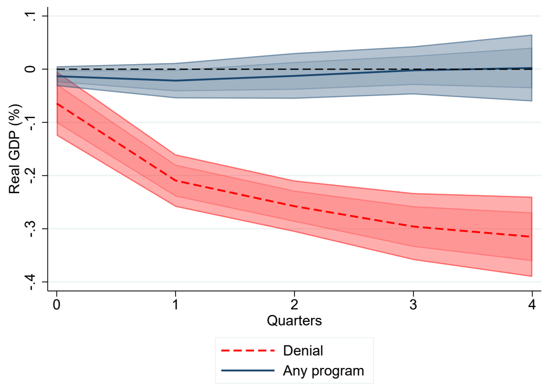


Figure B2. : Dynamic Response of Real GDP to a Natural Disaster: Denial vs Any Fiscal Help

Notes: Estimated changes in Quarterly Real GDP at horizons $h = 0, 1, 2, \ldots, 4$, following a natural disaster, depending on whether the disaster received fiscal assistance from FEMA. The sample period is 2006q1–2019q4. The shaded area denotes the 68% and 90% confidence intervals, based on state-level clustered standard errors.

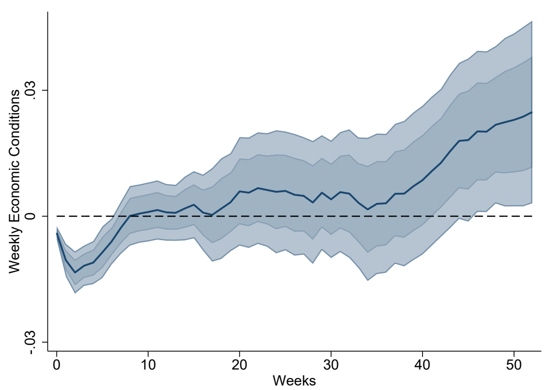
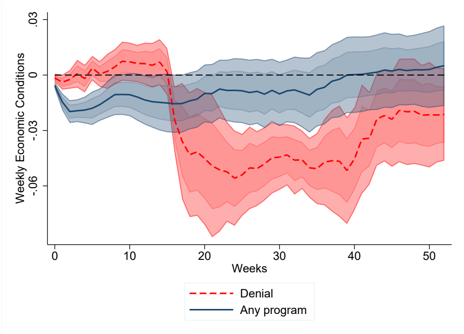
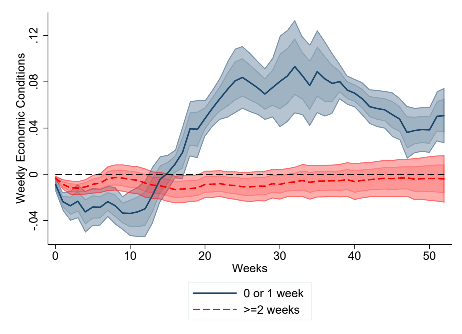


Figure B3. : Average Impact of Natural Disasters

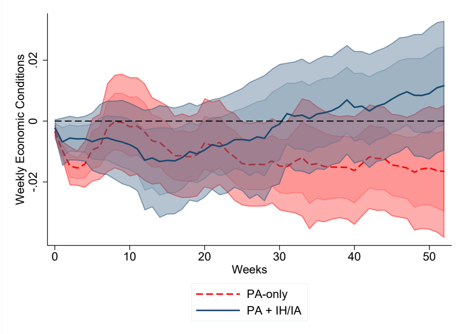
Notes: This figure displays the average impact of all disasters used in our analysis to estimate the effect of denial versus receiving any form of fiscal assistance. The sample period spans from 2006w1 to 2019w52.



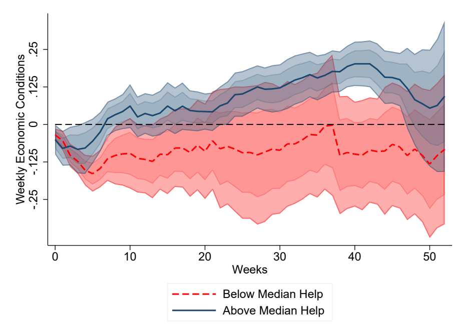
(a) Denial vs Any Fiscal Help.



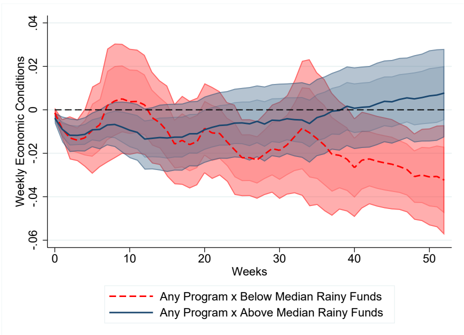
(b) By Lag in Fiscal Help.



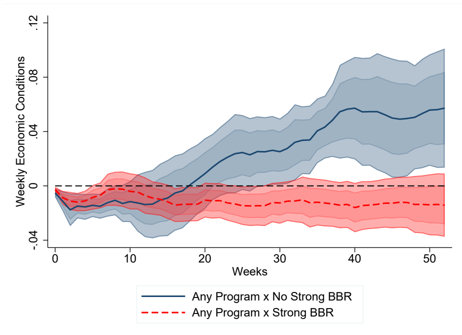
(c) By Program Status.



(d) By Total Help.



(e) Any Program and Rainy Day Funds.



(f) Any Program and Balanced Budget Rules.

Figure B4. : Robustness Analysis.

Notes: Estimated cumulative changes in the Weekly Economic Conditions Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 1, 2, \ldots, 52$, following a natural disaster. Sample 2006w1-2023w52. The shaded area denotes the 68% and 90% confidence intervals, based on state-level clustered standard errors.

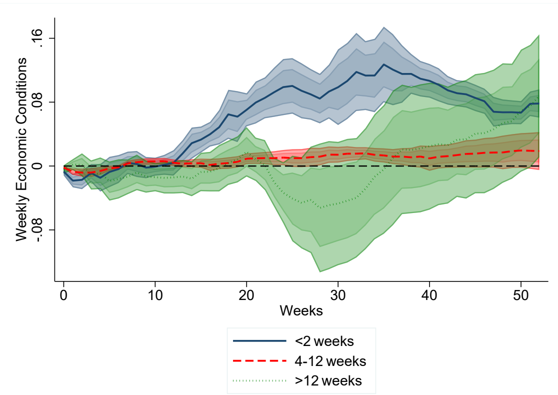
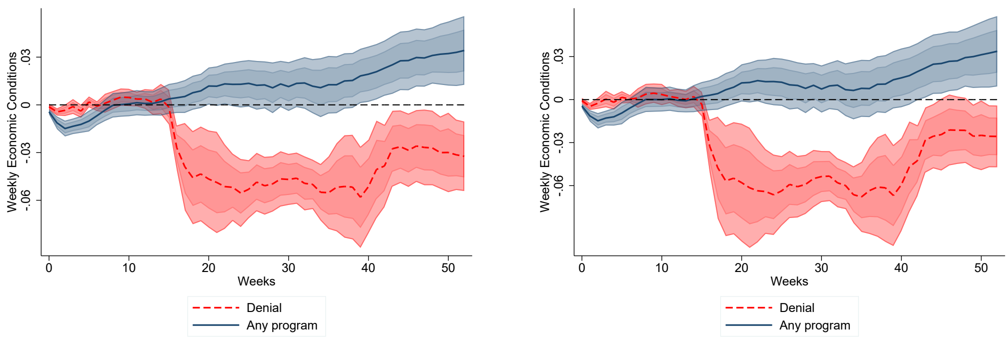


Figure B5. : Heterogeneity in the Delay of Fiscal Assistance

Notes: Estimated cumulative changes in the Weekly Economic Conditions Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 1, 2, \ldots, 52$, following a natural disaster. The figure explores heterogeneity in responses depending on the lag in fiscal assistance. The sample period is 2006w1–2019w52. The shaded area denotes the 68% and 90% confidence intervals, based on state-level clustered standard errors.

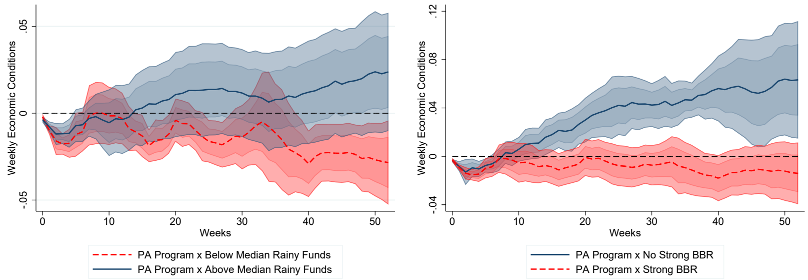


(a) Controlling for Hazard Mitigation

(b) Controlling for state-specific seasonality

Figure B6. : Robustness checks: controlling for past hazard mitigation funds and state-specific seasonality

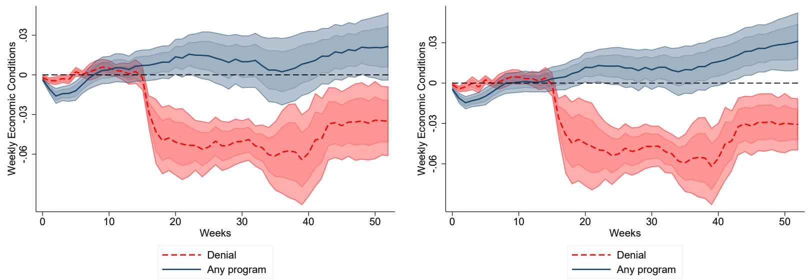
Notes: Estimated changes in the Weekly Economic Conditions Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 1, 2, \ldots, 52$ following a natural disaster, conditional on whether the event received FEMA fiscal assistance. Panel (a) additionally controls for lags of 1–52 weeks of a dummy equal to 1 when hazard-mitigation funds are received in state i at week t. Panel (b) replaces the baseline common seasonal dummies λ_t with state-specific seasonal dummies λ_{it}. The sample period is 2006w1–2019w52. Shaded bands denote the 68% and 90% confidence intervals based on state-level clustered standard errors.



(a) PA and Pre-Disaster Rainy Day Funds (b) PA and Pre-Disaster Balanced Budget Rules

Figure B7. : Dynamic Response of Economic Activity to a Natural Disaster: Heterogeneity in Fiscal Preparedness. Robustness analysis using only disasters that received public assistance (PA).

Notes: Estimated cumulative changes in the Weekly Economic Conditions Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 1, 2, \ldots, 52$ following a natural disaster. The sample period is 2006w1–2019w52. The shaded areas denote the 68% and 90% confidence intervals, based on state-level clustered standard errors. Panel (a) shows estimates depending on whether the affected state had a rainy day fund above or below the cross-sectional median in the week prior to the disaster. Panel (b) shows estimates depending on whether the affected state had a strong balanced budget rule in place in the week prior to the disaster.



(a) Excluding floods (b) Controlling for NFIP claims (total \$)

Figure B8. : Robustness checks: excluding floods and controlling for NFIP claims (total \$).

Notes: Estimated changes in the Weekly Economic Conditions Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 1, 2, \ldots, 52$ following a natural disaster, conditional on whether the event received FEMA fiscal assistance. The sample period is 2006w1–2019w52. The shaded areas denote the 68% and 90% confidence intervals, based on state-level clustered standard errors. Panel (a) redefines disasters to exclude floods. Panel (b) additionally controls for lags 1–8 of the total dollar amount of National Flood Insurance Program (NFIP) claims in state i at week t.

Table B4—: Selected Narratives of FEMA Denials

Date	Incidence of Denial	Ref.
October 6, 2008	Arizona Governor Janet A. Napolitano sought federal assistance for the Havasupai Tribe following flooding on Cataract Creek and the Havasupai Reservation (Aug. 15–17, 2008). The request was denied because it was submitted after the 30-day regulatory deadline and no extension had been requested, failing to meet 44 C.F.R. 206.36 requirements.	[1]
January 23, 2014	After the November 2013 Illinois tornado outbreak, engineer Gary Mauer described the 2014 county budget as unusually difficult due to uncertainty surrounding FEMA funding, citing significantly increased administrative burden and red tape issues.	[2]
March 3, 2014	FEMA denied Washington, Illinois Mayor Gary Manier's $26 million aid request following tornado damage. FEMA ruled certain debris removal and infrastructure damages ineligible and later determined that state damage assessments did not qualify for federal payment. Manier blamed federal guidelines for the calculation of damages.	[3]
September 20, 2017	Following the 2017 hurricane season, many Puerto Rico applicants faced denial due to difficulties proving homeownership stemming from informal property titles.	[4]
December 23, 2025	FEMA denied Wisconsin's request for Public Assistance and Hazard Mitigation funding after August floods, despite validated infrastructure damage exceeding $26.5 million. Robby Stoikes, WEM's Recovery Planning and Support Supervisor claimed that damages could not be computed in the time window of declaration. The state filed an appeal within the regulatory timeframe.	[5]
December 24, 2025	FEMA denied Arizona's request for funding following September 2025 floods. Local officials characterized the decision as premature given the ongoing assessment period.	[6]

Notes:
[1] Arizona Major Disaster Declaration Denial FEMA: `https://www.fema.gov/pdf/news/pda/120409$_$az$_$denial.pdf`
[2] The Grundy Register (2014). Coverage of FEMA funding challenges following 2013 tornado outbreak: `https://www.thegrundyregister.com/sites/default/files/Grundy%20Register%20012314.pdf`
[3] Wikipedia (2014) Washington, Illinois tornado: `https://en.wikipedia.org/wiki/2013_Washington\%2C$_$Illinois$_$tornado`
[4] García, I. (2022). Deemed Ineligible: Reasons Homeowners in Puerto Rico Were Denied Aid After Hurricane María. *Housing Policy Debate*, 32(1), 14–34.
[5] Vernon County Broadcaster (2025). `https://vernonreporter.com/wisconsin-appeals-fema-denial-of-public-assistance-after-august-floods/`
[6] AZFamily (2025). `https://www.azfamily.com/2025/12/23/fema-denies-disaster-aid-funding-gila-mohave-counties`

Preliminary Damage Assessment Data Collection

As part of our data construction effort, we collected and processed a comprehensive set of Preliminary Damage Assessments (PDAs) from FEMA's publicly accessible repository. PDAs are standardized reports jointly prepared by FEMA and state, local, tribal, and territorial (SLTT) authorities during the disaster declaration process. These documents provide detailed information on the nature, scope, and estimated impact of disaster events, irrespective of whether federal assistance was ultimately approved.

In total, we downloaded and reviewed the complete set of Preliminary Damage Assessment (PDA) reports available as of the end of 2023: 1,123 PDAs for disasters that received federal assistance and 187 PDAs for disasters that were denied assistance. These cases span the full range of disaster types classified by FEMA, including hurricanes, wildfires, droughts, winter storms, and floods. However, our analysis focuses specifically on weather-related events—namely, storms and floods—which account for the majority of high-impact disaster declarations in the U.S.

C1. Disasters Denied Federal Assistance

From an initial set of 187 PDAs corresponding to denied disaster requests—spanning natural disasters and non-natural incidents (e.g., chemical spills, civil unrest, explosions, and power outages)—we construct a final sample of 76 cases. This refined sample restricts the dataset to storms and floods, and excludes a couple of events for which key information (such as the disaster date or the statewide per-capita impact) is not reported in the PDA.

Of these 76 denial cases, 58 occurred on or before calendar week 52 of 2019 (`2019w52`) and form the baseline sample for our main analysis. The remaining 18 events, which occurred after `2019w52`, are excluded from the baseline specification but retained for robustness checks. Summary statistics for the 58 pre-2020 denial events are presented in Section 2 of the main paper.

C2. Disasters Receiving Federal Assistance

From the 1,123 PDAs corresponding to disasters that received federal assistance, we apply the same filtering criteria used for the denial sample. Specifically, we retain only disasters classified as storms or floods and exclude any cases where the PDA does not report the statewide per capita impact—a key variable in our empirical strategy.

Applying these filters yields a final sample of 480 approved disasters occurring between 2006 and 2023 that meet all inclusion criteria. Consistent with the denial sample, we restrict our baseline estimation to events that occurred on or before calendar week 52 of 2019 (`2019w52`), resulting in 435 approved disasters. These disasters comprise the group that received federal assistance in our main analysis and form the basis for the descriptive statistics presented in Section 2.

The remaining 45 disasters, which occurred after `2019w52`, are excluded from the baseline specification but included in robustness and supplementary analyses.

We link each approved disaster to FEMA's official disaster declaration database using the unique disaster identifier. This matching procedure enables us to augment the rich impact and cost data from the PDAs with additional variables from FEMA's database, including disaster type, date, geographic scope, and program-level aid indicators.

FEMA Institutional Background

FEMA's disaster operations are financed through the federal *Disaster Relief Fund* (DRF), a standing account replenished by Congressional appropriations. Because the DRF is nationally appropriated, there is no risk-rated premium or cross-state billing: the federal share of each declaration is paid from the DRF, while the affected jurisdiction covers its own non-federal match under the applicable program rules.

Cost sharing is program-specific. For *Public Assistance* (PA)—which funds debris removal, emergency protective measures, and the repair or replacement of public infrastructure—the federal share is not less than 75% of eligible costs, with the remaining share typically borne by states, tribes, territories, and/or local applicants. When warranted by incident severity, FEMA may recommend increasing the federal share (e.g., to 90%) and, for limited periods, authorizing 100% federal funding for emergency work categories, consistent with regulation and past practice. For *Individual Assistance* (IA) under the Individuals and Households Program, Housing Assistance is 100% federally funded, whereas Other Needs Assistance (ONA)—which covers personal property, transportation, and certain medical/dental costs—carries a 75% federal / 25% non-federal cost share that is prescribed by statute and cannot be waived by the President.

The pathway from impact to federal assistance is request-driven and evidence-based. Governors or Tribal Chief Executives submit a formal *Request for Presidential Disaster Declaration* (FEMA Form 010-0-13) that specifies the assistance types sought—PA, IA, and/or the Hazard Mitigation Grant Program—and the areas to be considered. FEMA and SLTT partners then conduct joint Preliminary Damage Assessments (PDAs) to document the nature and scope of impacts. Based on these PDAs, FEMA evaluates the request and recommends designations to the President. The request must be transmitted through the appropriate FEMA Regional Administrator within 30 days of the incident's occurrence or within 30 days after the end of the incident period, whichever is later, and must demonstrate that the situation exceeds state and local capabilities and that supplemental federal assistance is necessary. The Assistant Administrator for the Disaster Assistance Directorate may extend this 30-day deadline upon a written request submitted within the original filing period. Failure to comply with these procedural requirements may result in denial of a Major Disaster Declaration.

Evaluation criteria differ across IA and PA, which helps explain why decla-

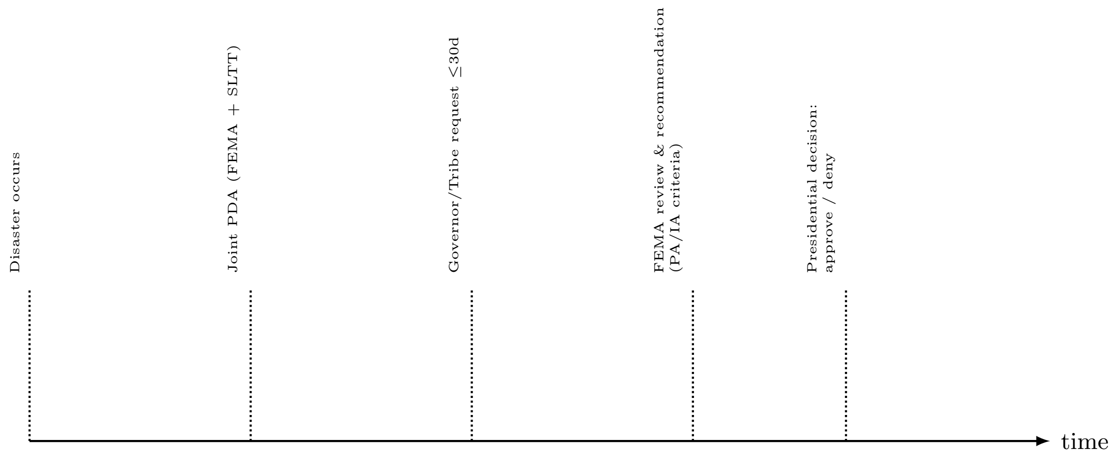


Figure D1. : FEMA disaster declaration timeline.

Note: The figure summarizes the sequence from disaster occurrence to a declaration decision. "Joint PDA" denotes the joint preliminary damage assessment conducted by FEMA and state, local, tribal, and territorial (SLTT) partners. The request must be submitted within 30 days of the incident's occurrence (or within 30 days after the incident period ends, whichever is later); extensions may be granted upon written request.

rations sometimes authorize one program but not the other. For IA, FEMA applies the six *Individual Assistance Declaration Factors* codified at 44 C.F.R. 206.48(b)—state fiscal capacity and resources, uninsured home and personal property losses, disaster-impacted population profile, impact to community infrastructure, casualties, and disaster-related unemployment. There is no single numeric trigger for IA; instead, the central question is whether survivors' unmet needs exceed state, local, and voluntary-agency capacity. By contrast, PA determinations emphasize statewide per-capita impact indicators that FEMA updates annually and documents during PDAs, while retaining qualitative flexibility to account for concentrated damage or critical-facility effects.

These institutional features produce predictable request patterns. When PDAs reveal substantial uninsured or underinsured household losses and the IA factors indicate capacity shortfalls, jurisdictions tend to request IA alongside PA. Conversely, events dominated by debris removal, emergency protective measures, and damage to public facilities often lead to PA-only requests, since the per-capita indicators and qualitative PDA findings are more readily satisfied on the public infrastructure side. Fiscal and administrative considerations also matter: the IA–ONA non-federal share of 25% is mandatory and not waivable, which some states and tribes weigh when deciding whether to seek IA. Finally, timing considerations frequently lead jurisdictions to request PA initially while PDAs continue, and then to seek addition of IA once evidence of unmet household needs becomes definitive.

PA and IA are authorized and funded independently. The two programs serve distinct purposes—households in the case of IA, and public infrastructure in the case of PA—so approval of one neither implies nor mechanically determines approval or funding amounts for the other. A given declaration may include PA only, IA only, or both.

Alternative Identification Strategy: Fuzzy RDD

This section describes the fuzzy regression discontinuity design (RDD) used to estimate the causal effect of FEMA program approval on weekly economic conditions following a disaster. We exploit the FEMA impact threshold as a source of quasi-experimental variation in program approval and trace out the dynamic response of economic conditions over the year after a disaster.

E1. Data and Sample

The analysis is based on a weekly panel of U.S. states, indexed by i for state and t for week. The sample covers all weeks up to the beginning of 2020. For the RD design, we focus on *disaster weeks*, defined as state-week observations in which at least one FEMA-recognized disaster occurs.

The estimation sample consists of disaster weeks whose associated disaster impact is close to the relevant FEMA threshold. Specifically, we construct a running variable

$$R_{it} \equiv \text{Impact}_{it} - \text{Threshold}_{it},$$

where Impact_{it} denotes the per-capita disaster impact in state i and week t, and Threshold_{it} is the corresponding FEMA eligibility cutoff. We restrict attention to disaster weeks within a symmetric bandwidth around the cutoff,

$$|R_{it}| \leq h, \qquad h = 0.75,$$

E2. Running Variable, Instrument, and Treatment

The discontinuity in program assignment is generated by whether the realized impact exceeds the FEMA threshold. We define the binary instrument

$$Z_{it} \equiv 1\{R_{it} \geq 0\},$$

which equals one when the disaster's impact is at or above the threshold and zero otherwise.

The treatment variable captures whether the state receives any FEMA program associated with the disaster that occurred in week t. Let D_{it} be an indicator equal to one if a FEMA program is approved and zero if the request is denied (no program approval). Program assignment is not perfectly determined by the threshold, so the design is *fuzzy*: crossing the cutoff raises the probability of treatment but does not deterministically assign it.

E3. Dynamic Outcome Definition

Let ECI_{it} denote the weekly economic conditions index in state i and week t. To study the dynamics of the response to FEMA program approval, we consider a sequence of horizon-specific outcomes

$$Y_{i,t+h} \equiv \mathrm{ECI}_{i,t+h}, \qquad h = 0, 1, \ldots, 52,$$

where h indexes the number of weeks after the disaster week t. The case $h = 0$ corresponds to contemporaneous conditions in the disaster week, while larger values of h capture short-, medium-, and longer-run effects up to one year after the disaster.

E4. Econometric Specification

The empirical specification follows a local linear fuzzy RDD with a common slope in the running variable. All regressions include state fixed effects γ_i, which absorb time-invariant state characteristics and capture level differences in weekly economic conditions across states.

First Stage

For a given horizon h, the first-stage relationship between treatment status and the instrument is

$$D_{it} = \alpha_{1h} + \tau_h Z_{it} + \beta_{1h} R_{it} + \gamma_i + u_{it+h}, \tag{E1}$$

estimated on the restricted sample of disaster weeks with $|R_{it}| \leq h$ for which $Y_{i,t+h}$ is observed. The coefficient τ_h measures the discontinuous jump in the probability of receiving any FEMA program at the threshold in the sample relevant for horizon h.

Second Stage

For each horizon $h = 0, 1, \ldots, 52$, we estimate a fuzzy RDD for the horizon-specific outcome via two-stage least squares:

$$Y_{i,t+h} = \alpha_{2h} + \beta_h D_{it} + \beta_{2h} R_{it} + \gamma_i + \varepsilon_{i,t+h}, \tag{E2}$$

where D_{it} is instrumented with Z_{it} as in equation (E1). The running variable enters linearly with a common slope on both sides of the cutoff, and state fixed effects γ_i are included in all specifications. Robust standard errors are reported.

The coefficient β_h is identified from the discontinuous change in treatment probability at the cutoff, controlling linearly for the running variable and for state fixed effects, and is estimated separately for each horizon h. The resulting sequence $\{\beta_h\}_{h=0}^{52}$ traces out the dynamic response of weekly economic conditions to FEMA program approval over the first year following a disaster. In parallel, we estimate equation (E2) with $Y_{it}^{(0,52)}$ as the outcome to obtain a single medium-run effect on the average ECI over the year after the disaster.

Table E1 reports the dynamic fuzzy RDD estimates of the effect of FEMA program approval on weekly economic conditions in the year following a disaster. The estimated treatment effects are positive at all horizons from the disaster week through 52 weeks after the event, with magnitudes that are economically meaningful and generally largest around 6–8 months after the disaster. While the precision of the estimates varies across horizons, coefficients in the intermediate range of 20–35 weeks are statistically significant at conventional levels, and the effect on the average ECI over the first 53 weeks is positive and marginally significant. Taken together, the pattern of estimates suggests that, conditional on experiencing a disaster near the FEMA eligibility threshold, receiving federal assistance is associated with a systematic and persistently higher level of economic activity over the subsequent year, rather than merely a short-lived boost in the immediate aftermath.

Table E1—: Dynamic fuzzy RDD estimates of FEMA program approval on ECI

Horizon h	2SLS estimate $\hat{\beta}_h$	Std. error	p-value
0	1.321*	0.748	0.077
1	1.240	0.793	0.118
2	1.161	0.777	0.135
3	1.163	0.776	0.134
4	1.101	0.764	0.150
5	1.191	0.756	0.115
6	1.149	0.743	0.122
7	1.260*	0.741	0.089
8	1.280*	0.762	0.093
9	1.137	0.739	0.124
10	1.000	0.706	0.156
11	1.018	0.696	0.144
12	0.959	0.682	0.160
13	1.095*	0.666	0.100
14	1.151*	0.681	0.091
15	1.141*	0.652	0.080
16	1.039	0.651	0.111
17	0.944	0.647	0.144
18	0.796	0.613	0.194
19	0.758	0.610	0.213
20	0.794	0.627	0.205
21	0.691	0.633	0.275
22	0.702	0.599	0.241
23	0.793	0.625	0.204
24	0.772	0.648	0.234
25	1.322*	0.705	0.061
26	1.306*	0.718	0.069
27	1.482*	0.777	0.056
28	1.387*	0.760	0.068
29	1.467*	0.764	0.055
30	1.418*	0.723	0.050
31	1.466**	0.708	0.038
32	1.460**	0.699	0.037
33	1.415**	0.706	0.045
34	1.402*	0.730	0.055
35	1.311*	0.712	0.065
36	1.162*	0.695	0.094
37	1.251*	0.674	0.063
38	1.123*	0.628	0.074
39	1.023	0.623	0.101
40	0.974	0.634	0.124
41	0.849	0.637	0.183
42	0.852	0.640	0.183
43	0.693	0.645	0.283
44	0.812	0.648	0.210
45	0.797	0.656	0.224
46	0.970	0.661	0.142
47	0.843	0.659	0.201
48	0.982	0.669	0.142
49	0.954	0.676	0.158
50	0.915	0.660	0.165
51	0.832	0.664	0.210
52	0.774	0.672	0.250
Avg 0–52	1.181*	0.656	0.072
First-stage F-statistic for instrument Z_{it} (1.above): $F - stat = 30.23$			

Notes: Each row reports the fuzzy RDD estimate of the effect of receiving any FEMA program (versus denial) on ECI h weeks after the disaster, or on the average ECI from t to $t+52$ for the last row. Estimates are from local linear specifications with a common slope in the running variable and state fixed effects. Robust standard errors are reported. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

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