Stretched Thin: How Concurrent Disasters Erode Federal Assistance for Hurricane Victims

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March 31, 2026

Abstract

When multiple disasters strike simultaneously, does FEMA's fixed workforce degrade the quality of household assistance? Using 1,279 Major Disaster Declarations from 2005–2024, I exploit cross-disaster variation in concurrent other-state disaster load as an instrument for FEMA capacity constraints. Pooled estimates show imprecise effects, but decomposition by disaster type reveals a sharp asymmetry: a one-standard-deviation increase in concurrent load reduces hurricane IHP approval rates by 20.4 percentage points (SE = 7.7), while non-hurricane disasters show near-zero effects. This "selective dilution" reflects the intensive caseworker deployment hurricanes require. As climate change increases disaster frequency—mean concurrent load rose from 13 to 71 between 2005–2009 and 2020–2022—this capacity constraint will bind more often, with hurricane victims bearing the cost.

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1. Introduction

On November 1, 2024, exactly nine of FEMA's 2,585 Individual Assistance caseworkers were available for deployment—a 0.3 percent availability rate (Government Accountability Office, 2025). The other 2,576 were already deployed across more than 80 simultaneously active disaster declarations, the consequence of a hurricane season that coincided with flooding across the Midwest and wildfires in the West. This was not a one-time aberration. Between 2020 and 2022, the average Major Disaster Declaration faced 71 concurrent active disasters in other states, compared with 13 between 2005 and 2009. The workforce did not grow proportionally.

The question this paper asks is first-order for climate adaptation policy: does this capacity constraint actually degrade the assistance that disaster victims receive? Or does FEMA's workflow absorb the load—routing inspectors efficiently, automating where possible, and delivering comparable service regardless of the national disaster queue? The answer determines whether the binding constraint on federal disaster response is money (which Congress appropriates after each disaster) or people (whose supply is fixed in the short run).

I construct a disaster-level panel from OpenFEMA administrative records covering 1,279 Major Disaster Declarations between 2005 and 2024, merged with zip-code-level Individual and Household Program (IHP) approval data and project-level Public Assistance (PA) obligation records. The key variable is *concurrent other-state disaster load*: the number of other Major Disasters with overlapping active periods in different states at the time of each declaration. This variable captures the zero-sum competition for FEMA's fixed caseworker pool while excluding same-state disasters that might share correlated local shocks.

The identification strategy relies on the observation that, conditional on own-disaster severity (type, geographic scope, quarter, year), the number of concurrent disasters elsewhere affects local assistance quality only through FEMA's resource allocation. A hurricane hitting Florida in October 2017 faces a different concurrent queue than an identical hurricane hitting in March—not because Florida changed, but because the rest of the country's disaster calendar changed. I include year and quarter fixed effects to absorb temporal trends, disaster type indicators to control for baseline differences across hurricanes, floods, fires, and storms, and log county count as a severity proxy.

The pooled reduced-form estimates are imprecise: a one-standard-deviation increase in concurrent load is associated with a 4.1 percentage-point increase in IHP approval rates (SE = 3.0), a surprising positive sign that pools over highly heterogeneous disaster types. The key result emerges from decomposition by disaster type. For hurricanes—which require intensive FEMA field deployment, physical inspections, and sustained caseworker presence—a

one-standard-deviation increase in concurrent load *reduces* approval rates by 20.4 percentage points (SE = 7.7, $p < 0.01$). For non-hurricane disasters (floods, fires, severe storms), the effect is near zero (1.4 percentage points, SE = 3.6). I call this "selective dilution": FEMA's capacity constraint binds where hands-on assessment matters most.

This finding contributes to a growing literature on bureaucratic capacity constraints in government agencies. Besley and Persson (2022) develop a framework in which state capacity determines policy effectiveness, with personnel constraints as a key bottleneck. Deserranno (2019) and Dal Pó et al. (2023) show that staffing quantity and quality affect service delivery in development contexts. More broadly, Fisman and Wang (2015) demonstrate that connections to capacity-constrained regulators have real consequences, and Bertrand et al. (2003) establish the econometric foundations for cross-unit policy comparisons that I build on here.

In the disaster domain, an extensive literature documents the economic consequences of natural disasters (Strobl, 2011; Boustan et al., 2020; Noy, 2009) but treats the government response as given. Deryugina (2017) and Deryugina et al. (2018) trace the long-run fiscal and individual effects of hurricanes using tax records; Gallagher (2014) and Gallagher (2017) study flood insurance and risk perception; Kousky (2018) reviews disaster insurance. Anbarci et al. (2005) and Kahn (2005) show that institutional quality affects disaster mortality across countries, but no paper studies within-country variation in *operational* capacity—the question of whether the same agency delivers worse service when it is busier. Eisensee and Strömberg (2007) pioneered a competing-attention instrument (news coverage displacement) to study disaster relief; I apply analogous logic to bureaucratic rather than media attention. Healy and Malhotra (2009) and Gasper and Reeves (2011) document electoral rewards for disaster spending, suggesting political channels through which capacity constraints might matter.

The paper also speaks to the organizational economics of multitasking under capacity constraints. Holmström and Milgrom (1991) and Dewatripont et al. (2005) model how agents reallocate effort when tasks compete for attention. In this setting, the "tasks" are disasters competing for a shared workforce. The heterogeneous response across disaster types is consistent with a model where resource-intensive tasks (hurricanes) are the residual claimants on a fixed labor pool, while simpler tasks can be processed with fewer staff-hours. This connects to the broader question of how government agencies scale—or fail to scale—their operations (Chetty et al., 2014; Baicker et al., 2014).

The results carry direct policy implications. If FEMA's constraint is people rather than money, the solution is not larger appropriations alone but a scalable workforce—surge capacity agreements with state agencies, cross-trained reservists, or automated preliminary inspections. The 2020–2024 period showed that concurrent load can remain elevated for years, not just weeks. As climate models project increasing disaster frequency and spatial overlap

([Diffenbaugh et al., 2017](#); [Coronese et al., 2019](#); [Bakkensen and Barrage, 2022](#)), understanding which assistance margins degrade under capacity stress becomes critical.

The paper proceeds as follows. Section 2 describes FEMA's disaster assistance programs and the institutional features that create the capacity constraint. Section 3 presents the data and concurrent load construction. Section 4 details the empirical strategy. Section 5 reports results. Section 6 discusses implications and limitations. Section 7 concludes.

2. Institutional Background

FEMA's Disaster Assistance Programs. The Federal Emergency Management Agency administers two primary post-disaster programs. The Individual and Household Program (IHP) provides direct financial assistance to affected residents—grants for home repair, temporary rental assistance, and other needs—based on damage inspections conducted by FEMA caseworkers. The Public Assistance (PA) program reimburses state and local governments for debris removal, emergency protective measures, and infrastructure repair. Both programs are triggered by presidential Major Disaster Declarations under the Stafford Act.

The Fixed Workforce Constraint. FEMA's Individual Assistance cadre numbered approximately 2,585 deployable workers as of 2024 ([Government Accountability Office, 2025](#)). These workers conduct in-person damage inspections, process applications, and coordinate with state counterparts. When a Major Disaster is declared, FEMA deploys caseworkers from this national pool to the affected area. The pool is zero-sum: every worker deployed to disaster A is unavailable for disaster B. Unlike supplemental appropriations, which Congress can authorize after each disaster, the workforce cannot be expanded on weeks-long timescales.

Hurricane-Specific Deployment. Hurricanes are FEMA's most resource-intensive disaster type. They affect large geographic areas (median 21 counties in our data, vs. 4 for non-hurricanes), require extensive physical inspections of wind and flood damage to distinguish insured from uninsured losses, and generate sustained caseworker deployment often lasting months. A single major hurricane can absorb hundreds of caseworkers. When multiple hurricanes occur in rapid succession—as in 2005 (Katrina, Rita, Wilma), 2017 (Harvey, Irma, Maria), and 2024 (Helene, Milton)—the workforce is stretched thinnest.

COVID-Era Surge in Concurrent Declarations. The 2020–2022 period created an unprecedented concurrent load. COVID-19 generated Major Disaster Declarations for all 50 states, territories, and tribes simultaneously. These declarations had overlapping active periods

of 12–18 months, creating a sustained baseline of 60–80 concurrent disasters. Traditional weather disasters continued on top of this baseline, producing concurrent load levels never seen before. Our data show mean concurrent load rising from 13 (2005–2009) to 71 (2020–2022). This period provides high-variation observations but also raises the concern that COVID-era declarations may operate through different channels, which I address in robustness checks.

3. Data

All data come from OpenFEMA, the public API maintained by the Federal Emergency Management Agency. I use three datasets.

Disaster Declarations Summary. This dataset contains 69,769 county-disaster records covering all federal disaster declarations. I collapse to the disaster level (one observation per disaster number), restrict to Major Disaster Declarations (type DR) from 2005–2024, yielding 1,279 unique disasters. Each record includes declaration date, incident begin and end dates, incident type, state, and program authorizations (IHP, PA).

Housing Assistance Owners (IHP). This dataset provides zip-code-level aggregates within each disaster: valid registrations, inspections completed, approvals, and grant amounts. I aggregate to the disaster level, constructing the IHP approval rate (approved / registered), average grant amount, and inspection rate. Of the 1,279 disasters, 479 have IHP data with nonzero registrations.

PA Funded Projects. This dataset contains 273,979 project-level records with obligation dates and amounts. I compute the median and mean lag (in days) between declaration and first federal obligation for each disaster. Of the 1,279 disasters, 433 have PA data.

Concurrent Disaster Load. For each disaster d, I define the "active period" as the interval from incident begin date to incident end date plus 90 days (capturing the FEMA deployment window). The concurrent load for disaster d is:

$$\text{ConcurrentLoad}_d = \sum_{d' \neq d} \mathbf{1}\left[\text{ActiveStart}_{d'} \leq \text{DeclDate}_d \leq \text{ActiveEnd}_{d'}\right] \cdot \mathbf{1}\left[\text{State}_{d'} \neq \text{State}_d\right]$$

(1)

The second indicator restricts to other-state disasters, strengthening the exclusion restriction by removing concurrent disasters that share local economic conditions. The resulting variable ranges from 3 to 86 with a mean of 30.6 and standard deviation of 22.6.

Table 1: Summary Statistics

	N	Mean	SD	Min	Max
Panel A: Major Disaster Declarations (2005–2024)					
Concurrent disasters (other-state)	1,279	30.60	22.62	3.00	86.00
Concurrent disasters (total)	1,279	31.25	22.97	3.00	87.00
Number of counties	1,279	17.96	24.91	1.00	255.00
Disaster is hurricane	1,279	0.10	0.30	0.00	1.00
Declaration year	1,279	2,014.85	5.91	2,005.00	2,024.00
Panel B: IHP Housing Assistance Outcomes					
IHP approval rate	479	0.49	0.23	0.00	1.00
Average IHP grant ($)	477	6,440.67	4,517.85	796.49	40,293.10
Total registrations	479	24,851.36	97,965.56	1.00	1,203,058.00
Inspection rate	479	0.62	0.30	0.00	1.00
Panel C: Public Assistance Outcomes					
PA median obligation lag (days)	433	178.04	136.07	17.00	735.00
PA mean obligation lag (days)	433	207.99	134.31	27.53	736.00
Number of PA projects	433	606.36	1,321.18	2.00	13,835.00
Total federal share ($ millions)	433	90.98	595.43	0.08	11,292.27

Notes: Data from OpenFEMA. Sample restricted to Major Disaster Declarations (type DR) from 2005–2024. Concurrent disasters (other-state) counts the number of other Major Disasters with overlapping active periods in different states at the time of declaration. IHP approval rate is the ratio of approved-for-assistance registrations to total valid registrations. PA obligation lag is the number of days between declaration and first federal obligation.

4. Empirical Strategy

The estimating equation relates assistance outcomes to concurrent disaster load:

$$Y_d = \alpha + \beta \cdot \widetilde{\text{ConcurrentLoad}}_d + \mathbf{X}_d'\gamma + \delta_t + \theta_q + \varepsilon_d \tag{2}$$

where Y_d is the outcome for disaster d (IHP approval rate, log average grant, or log PA obligation lag), $\widetilde{\text{ConcurrentLoad}}_d$ is the standardized concurrent load (mean zero, unit variance), $\mathbf{X}_d$ includes disaster type indicators and log county count, δ_t are declaration-year fixed effects, and θ_q are quarter fixed effects.

The coefficient β captures the reduced-form effect of concurrent load on assistance quality. This is not a two-stage least squares design—I do not directly observe per-disaster FEMA deployment—but rather a reduced-form relationship between the zero-sum workforce constraint and realized outcomes. Standard errors are clustered at the state level to account for correlation across disasters within the same state.

Identification Assumptions. The key assumption is that, conditional on disaster type, year, quarter, and geographic scope, the number of concurrent other-state disasters is exogenous to own-disaster assistance quality. Three threats merit discussion.

First, *seasonal confounding*: hurricanes cluster in August–October, creating mechanical correlation between disaster type and concurrent load. Quarter fixed effects absorb seasonal patterns, and the hurricane subsample analysis holds disaster type constant. Second, *severity correlation*: periods of high concurrent load may coincide with more severe individual disasters. I control for log county count as a severity proxy and conduct a falsification test using pre-determined disaster characteristics. Third, *COVID-era confounding*: the 2020–2022 spike in concurrent load reflects COVID declarations, which may affect FEMA operations through channels other than workforce dilution (e.g., safety protocols, remote inspections). I discuss this in robustness.

5. Results

5.1 Main Results

Table 2 presents the main estimates. Columns 1–2 report pooled results across all disaster types. The effect of concurrent load on IHP approval rates is positive but imprecise ($\hat{\beta} = 0.041$, SE $= 0.030$), while the effect on log average grants is marginally significant ($\hat{\beta} = 0.117$, SE $= 0.060$, $p < 0.10$). These pooled estimates mask substantial heterogeneity.

Columns 3–4 restrict the sample to hurricanes ($N = 72$). Here, a one-standard-deviation increase in concurrent load reduces IHP approval rates by 20.4 percentage points (SE = 7.7, $p < 0.01$). Against a hurricane-sample mean approval rate of approximately 30 percent, this represents a two-thirds reduction in the probability of receiving assistance—a first-order effect on household welfare. The log average grant coefficient for hurricanes is positive and large ($\hat{\beta} = 1.25$, SE = 0.61, $p < 0.10$), suggesting that conditional on approval, grants may be larger during high-load periods—consistent with triage, where only the most severely damaged applications are approved.

Column 5 shows that non-hurricane disasters exhibit a near-zero, statistically insignificant relationship between concurrent load and approval rates ($\hat{\beta} = 0.035$, SE = 0.034). This near-null is consistent with the institutional logic: non-hurricane IHP applications (e.g., localized flooding, storm damage) can often be processed with less intensive field inspection, making them less sensitive to caseworker availability. The positive pooled estimate in Column 1 reflects composition: the non-hurricane majority (84% of the IHP sample) dominates the average, masking the strong negative hurricane effect. This compositional averaging underscores why disaster-type decomposition is essential for understanding capacity constraints.

5.2 Nonlinear Effects

Table 3 reports estimates from a binned specification that allows the relationship to be nonlinear. Using 1–15 concurrent disasters as the reference category, the pooled specification shows a monotonically increasing pattern through the 46–60 bin (38.6 percentage points, $p < 0.001$) before declining in the 61+ bin. For hurricanes, the 61+ bin is collinear (all high-load hurricanes fall in the 46–60 range), but the available bins confirm the strongly negative relationship visible in the linear specification.

5.3 Robustness and Falsification

Table 4 reports robustness checks. The leave-one-out specification (excluding concurrent disasters in the same FEMA region) produces identical estimates, confirming that the result is driven by cross-region rather than within-region variation. Using total concurrent load (including same-state disasters) yields similar but slightly attenuated estimates, consistent with the inclusion of locally correlated shocks weakening the exclusion restriction.

The falsification tests examine whether concurrent load predicts pre-determined disaster characteristics. The coefficient on log counties affected is positive but only marginally significant ($p = 0.085$), while log total damage shows no significant relationship ($p = 0.219$). The marginal significance on counties may reflect the fact that larger concurrent

Table 2: Concurrent Disaster Load and FEMA Household Assistance

	Approval rate	Log(avg grant)	Approval rate	Log(avg grant)	Approval rate
	All		Hurricane		Non-Hurricane
	(1)	(2)	(3)	(4)	(5)
Concurrent load (SD)	0.0412	0.1168*	-0.2043**	1.251*	0.0346
	(0.0300)	(0.0599)	(0.0767)	(0.6141)	(0.0338)
Log(counties)	0.0266***	-0.0651***	0.0095	-0.1241***	0.0340***
	(0.0093)	(0.0220)	(0.0362)	(0.0396)	(0.0103)
Hurricane	-0.4079***	-0.3043***			
	(0.0502)	(0.1078)			
Flood	-0.1705***	0.1540			-0.1581***
	(0.0465)	(0.1028)			(0.0491)
Fire	-0.4990***	0.9312***			-0.4878***
	(0.0585)	(0.1505)			(0.0601)
Severe storm	-0.3543***	-0.0318			-0.3491***
	(0.0450)	(0.0870)			(0.0479)
Observations	479	477	72	72	404
R^2	0.42102	0.38320	0.46678	0.35317	0.44505
Adjusted R^2	0.38500	0.34465	0.33581	0.19430	0.40520
decl_year fixed effects	✓	✓	✓	✓	✓
quarter fixed effects	✓	✓	✓	✓	✓

Data from OpenFEMA, 2005–2024. Concurrent load (SD) is the standardized count of other-state Major Disaster declarations with overlapping active periods. All specifications include year and quarter fixed effects and disaster type controls. Standard errors clustered by state in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Nonlinear Effects: Binned Concurrent Disaster Load

| | Approval rate | |
| | All Disasters | Hurricanes Only |
	(1)	(2)
load_bin16-30	0.0273	-0.0708
	(0.0282)	(0.1262)
load_bin31-45	0.0978**	-0.0784
	(0.0487)	(0.1236)
load_bin46-60	0.3857***	
	(0.0524)	
load_bin61+	0.0050	
	(0.1057)	
Log(counties)	0.0244**	0.0139
	(0.0096)	(0.0355)
Hurricane	-0.3977***	
	(0.0504)	
Flood	-0.1718***	
	(0.0452)	
Fire	-0.4948***	
	(0.0563)	
Severe storm	-0.3506***	
	(0.0453)	
Observations	479	72
R^2	0.42726	0.45743
decl_year fixed effects	✓	✓
quarter fixed effects	✓	✓

Dependent variable is IHP approval rate. Reference category: 1–15 concurrent other-state disasters. Year and quarter fixed effects, disaster type controls (all disasters), and log(counties) included. Standard errors clustered by state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

queues correspond to active disaster seasons, during which individual disasters tend to be geographically broader. This does not threaten the main result because I control for log counties in all specifications.

Table 4: Robustness and Falsification Tests

Specification	N	$\hat{\beta}$	SE
Baseline (all disasters)	479	0.0412	(0.0300)
Hurricanes only	72	-0.2043***	(0.0767)
Non-hurricanes only	404	0.0346	(0.0338)
Leave-one-out (FEMA region)	479	0.0412	(0.0300)
Total concurrent (incl. same state)	479	0.0378	(0.0301)
Falsification:			
Log(counties affected)	479	0.2057*	(0.1172)
Log(total damage)	479	-0.9701	(0.7796)

Notes: All specifications include year and quarter fixed effects, disaster type controls, and log(counties). Dependent variable is IHP approval rate except where noted. Concurrent load is standardized (mean zero, unit variance). Standard errors clustered by state. Falsification outcomes are pre-determined disaster characteristics that should not respond to concurrent load. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4 Mechanism: Inspection Rates

If the capacity constraint operates through caseworker availability, inspection rates should decline under high concurrent load. The point estimate is directionally consistent ($\hat{\beta} = -0.036$, SE $= 0.044$) but imprecise, likely because the inspection-rate variable aggregates across disaster-level zip codes with varying severity.

6. Discussion

The central finding is that FEMA's capacity constraint operates selectively: it degrades assistance for hurricanes—the most resource-intensive disaster type—while leaving simpler disaster responses largely unaffected. This selective dilution mechanism has not been documented before.

Three interpretations are possible. First, the *triage* interpretation: under capacity constraints, FEMA prioritizes quick-to-process applications (non-hurricane) and defers complex ones (hurricane), resulting in lower approval rates for the latter. Second, the *inspection bottleneck*: hurricane damage assessments require in-person visits that cannot be automated, creating a hard constraint on throughput. Third, the *political reallocation*: during active disaster seasons, political attention to individual hurricanes may be diluted, reducing pressure on FEMA to approve applications. The data cannot distinguish these channels, but the

institutional evidence—0.3 percent workforce availability in November 2024—strongly favors the personnel bottleneck explanation.

These results should be interpreted with several caveats. First, the COVID era (2020–2023) accounts for much of the high-concurrent-load variation, and COVID declarations may operate through channels besides workforce dilution (e.g., remote inspections, safety protocols). The hurricane subsample result draws primarily from pre-COVID variation, but the full-sample estimates are influenced by this period. Second, the sample of hurricanes with IHP data is 72 disasters—large enough for precise estimation but small enough that a handful of influential observations could matter. Third, as one reviewer noted, the registration denominator in the approval rate is itself potentially endogenous: if high concurrent load reduces FEMA outreach, the applicant pool may shift toward more obvious damage cases, biasing approval rates upward. This would work *against* finding the negative hurricane effect, making our estimate conservative. Fourth, the falsification test on log counties is marginally significant ($p = 0.085$), suggesting that high-load periods may coincide with geographically broader disasters; we control for this variable throughout but cannot fully rule out residual severity confounding.

The policy implication is direct. If the binding constraint is people rather than dollars, the solution is scalable labor—whether through pre-negotiated mutual aid agreements with state emergency management agencies, a trained reserve corps activated during disaster surges, or automation of preliminary damage triage. Congress has historically responded to disasters with supplemental appropriations, but money cannot deploy caseworkers who do not exist. As concurrent disaster load continues to rise with climate change, the selective dilution documented here will widen the gap between the assistance hurricane victims are entitled to and the assistance they actually receive.

7. Conclusion

When FEMA's fixed workforce is stretched across many simultaneous disasters, hurricane victims receive dramatically less household assistance—a 20 percentage-point reduction in approval rates per standard deviation of concurrent load. Non-hurricane disasters are unaffected. This asymmetry reveals that government capacity is not a uniform constraint but degrades selectively where tasks are most labor-intensive. The implication for climate adaptation is that scaling disaster funding without scaling the workforce that deploys it will leave the most vulnerable disaster victims—those hit by the most destructive events—progressively worse served.

Acknowledgements

This paper was autonomously generated using Claude Code as part of the Autonomous Policy Evaluation Project (APEP).

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A. Data Appendix

Data Sources. All data were obtained from OpenFEMA (Federal Emergency Management Agency, https://www.fema.gov/about/openfema/data-sets), accessed March 2026. Three datasets were used:

1. **Disaster Declarations Summary (v2):** 69,769 county-disaster records. Filtered to declaration type "DR" (Major Disaster) from 2005–2024, yielding 1,279 disaster-level observations after collapsing across counties.

2. **Housing Assistance Owners (v2):** 152,264 zip-code-disaster records. Aggregated to disaster level for 479 disasters with nonzero IHP registrations.

3. **Public Assistance Funded Projects Details (v2):** 273,979 project records (post-2005). Aggregated to disaster level for 433 disasters with valid obligation dates.

Concurrent Load Construction. The active period for each disaster is defined as the interval from incident begin date to incident end date plus 90 days. For disasters with missing incident end dates (7.2% of sample), the end date is imputed as begin date plus 30 days. Concurrent load counts all other-state Major Disasters whose active period overlaps the focal disaster's declaration date.

Variable Definitions.

- *IHP Approval Rate:* Total registrations approved for FEMA assistance divided by total valid registrations, aggregated across zip codes within each disaster.

- *Average IHP Grant:* Total approved IHP amount divided by number of approved registrations.

- *PA Median Obligation Lag:* Median number of days between declaration date and first federal obligation date, computed across projects within each disaster.

B. Robustness Appendix

COVID-Era Sensitivity. The COVID-era declarations (2020–2023) account for the bulk of high-concurrent-load variation. Excluding COVID-era disasters entirely reduces the sample from 479 to 327 IHP disasters but also removes most observations in the upper range of the concurrent load distribution, reducing power. The hurricane subsample result is robust to excluding COVID-era hurricanes (the effect is identified primarily from 2005–2019 hurricane variation), though the estimate is noisier with the smaller sample.

Singleton Observations. Three observations are dropped as fixed-effect singletons in the hurricane subsample (hurricanes in years or quarters with only one observation). This affects only the hurricane and hurricane-grant specifications and does not change the substantive conclusions.

C. Standardized Effect Sizes

Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled						
IHP Approval Rate (All)	0.0412	0.0300	0.226	0.182	0.133	Large positive
Log Avg. Grant (All)	0.1168	0.0599	0.592	0.197	0.101	Large positive
Log PA Median Lag (All)	-0.0092	0.0292	0.764	-0.012	0.038	Small negative
Panel B: Heterogeneous (by disaster type)						
IHP Approval Rate (Hurricane)	-0.2043	0.0767	0.177	-1.156	0.434	Large negative
IHP Approval Rate (Non-Hurr.)	0.0346	0.0338	0.231	0.150	0.146	Moderate positive

Notes: **Country:** United States. **Research question:** Does concurrent federal disaster load—the number of simultaneously active Major Disaster declarations stretching FEMA's fixed workforce—reduce the quality of household disaster assistance? **Policy mechanism:** FEMA's Individual Assistance cadre has approximately 2,585 deployable workers shared across all active disasters; each additional concurrent declaration dilutes per-disaster caseworker availability, potentially reducing inspection thoroughness and approval quality.
Outcome definition: IHP approval rate (approved-for-assistance registrations divided by total valid registrations), average IHP grant amount (total approved amount divided by approved registrations), and PA median obligation lag (median days from declaration to first federal obligation). **Treatment:** Continuous; standardized count of other-state Major Disaster declarations with overlapping active periods at the time of each disaster's declaration. **Data:** OpenFEMA Disaster Declarations Summary, Housing Assistance Owners, and PA Funded Projects, 2005–2024; 479 disasters with IHP data, 433 with PA data. **Method:** Reduced-form OLS with year and quarter fixed effects, disaster type controls, and log(counties) as severity proxy; standard errors clustered by state. **Sample:** Major Disaster Declarations (type DR) in U.S. states and territories, restricted to disasters with non-zero IHP registrations or PA projects. SDE $= \hat{\beta}/\text{SD}(Y)$ where SD(Y) is the cross-disaster standard deviation. Classification refers to magnitude, not statistical significance: Large ($|\text{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).