Natural Disasters and Infrastructure Insurance: Fiscal Multipliers, House Prices, and Local Public Finance

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Abstract

Natural catastrophes destroy public infrastructure that is critical to local economic recovery, generally uninsured, and repaired primarily through federal transfers. Using an instrumental variable, I show the marginal $100 per capita of repair generates large gains: per capita income rises 2.5%, unemployment falls 0.4 percentage points, new business applications rise 8.3%, and house prices rise 5.2%. Federal aid eases local fiscal constraints: debt falls 15%, tax rates fall 7.6%, and the tax base expands by 0.5%. A spatial-equilibrium model values welfare at $4.62 per federal dollar. Federal infrastructure repair acts as partial insurance for disaster-exposed localities.

JEL Codes: H84, H71, Q54, R11, E62

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1. Introduction

Natural disasters destroy local public infrastructure. Roads, bridges, water systems, schools, and public buildings connect workers to jobs, firms to markets, and households to basic services. Economic recovery depends on whether this public capital stock is restored. Over the past two decades, US natural disasters have caused more than $2 trillion in property damage, including more than $300 billion in damage to public infrastructure. The federal Public Assistance program (PA), the primary vehicle for repairing damaged public facilities, spent $170 billion over the same period.[1] Yet the marginal value of this reconstruction remains largely unknown. Public Assistance may simply shift rebuilding costs from local to federal balance sheets, or it may determine whether damaged public capital is restored at all.

I show that the marginal dollar of federal infrastructure repair has large effects on local recovery. The estimates reconcile two puzzling empirical patterns. Federally declared disasters are sometimes followed by stronger local income growth, suggesting that post-disaster transfers may more than offset the direct losses from the shock (Roth Tran and Wilson, 2025). Yet among disaster-declared places, counties receiving more federal aid do not recover faster in the cross section. This is because assistance flows to places with greater damage and worse counterfactual outcomes, and so the returns to rebuilding are confounded with the severity of the disaster. Once this selection problem is addressed, the marginal federal dollar raises income, employment, house prices, and business activity, generating a gross income multiplier of roughly $9 per dollar of cumulative PA.

If they are so valuable, why do local governments not finance these repairs themselves? Because disasters sharply constrain local fiscal capacity (Jerch et al., 2023; Auh et al., 2022). Federal assistance directly eases this constraint: debt, tax rates, and borrowing costs all fall. This contrasts with other settings, such as federal highway aid, where additional federal dollars simply crowd out local and state spending (Knight, 2002). Disaster recovery differs because federal aid arrives after a locally concentrated public-capital shock, when the local tax base and borrowing capacity are impaired. Hence, by providing aid precisely when local finances

[1] NOAA National Centers for Environmental Information, US Billion-Dollar Weather and Climate Disasters; Congressional Budget Office, *FEMA's Disaster Relief Fund: Budgetary History and Projections*, 2023; FEMA Public Assistance Funded Projects Details.

are most stretched, PA uses the federal balance sheet to smooth risk and insure localities against disasters.

Estimating the causal effect of infrastructure repair on local outcomes is difficult because disaster severity drives both aid and economic decline. I address this with an instrumental variable strategy that exploits how FEMA's administrative capacity scales with disaster size. When a presidentially declared disaster is severe and covers many counties, FEMA opens a Joint Field Office and deploys Public Assistance Coordinators, project specialists, and engineers to support local governments through the application process - formulating projects, drafting cost estimates, navigating eligibility determinations, and shepherding requests through review (McCarthy, 2014). A larger disaster mobilizes more of this capacity, so, holding fixed the level of own damage, a county receives substantially more aid when the disaster is widespread than when it is localized. This mobilization is directly observable. In FEMA's own procurement records, the contracting that supports a disaster's field operation - technical assistance consultants, field office space, inspections - follows the same pattern: holding own damage fixed, a county whose peers were one standard deviation more damaged hosts approximately 13 percent more of it within a year of the declaration (Figure 3). I therefore instrument a county's level of aid received with the per-capita damage to all other disaster-damaged counties in the state.

The instrument requires that peer damage affects the focal county's economy only through its effect on infrastructure-aid allocation. I consider three potential violations and rule out each. First, peer counties that share a disaster declaration are often geographically proximate, so their damage could directly harm the focal county's economy through disrupted trade and commuting linkages. I rule this out by recomputing the instrument with adjacent peer counties excluded. Second, high peer damage could proxy for other federal resources directed to the focal county, capturing the generalized effects of federal assistance programs rather than PA itself. I rule this out by showing that the instrument does not predict total government transfers or any other federal disaster program (NFIP claims, SBA disaster loans, or Individual Assistance) conditional on own damage. Third, Public Assistance spending in the focal county could spill over to neighboring counties, violating SUTVA. I rule this out by directly testing for spillovers - regressing each neighbor's outcomes on the focal county's instrumented PA - and broadly find-

ing null effects. Separately, because assessed disaster damage is measured with error, I rebuild both the instrument and the damage controls from physically modeled flood and wind intensity constructed independently of FEMA's assessment. The results are unchanged, whether identified between disasters or from variation across counties within the same disaster - ruling out measurement error that is disaster-specific or common to FEMA's damage estimates across counties.

Properly identified, I find that repairing infrastructure has large effects on local employment, income, business activity, and house prices. An additional $100 of PA per capita - about twice the average amount received in my sample - raises per capita income by 2.5%, total income by 3.3%, and lowers the unemployment rate by 0.4 percentage points. The 0.8 percentage point gap between per capita and total income is due to an estimated net 0.67% population gain. Behind these gains is broader entrepreneurial and reconstruction activity: business applications rise 8.3% and the number of operating establishments rises 2.4%. House prices rise by 5.2% - the local housing market capitalizing higher incomes, employment, business activity, lower tax rates, and rebuilt public capital into asset value. Overall, the income response implies a local fiscal multiplier of roughly $9 per dollar of cumulative PA - four to six times the cross-sectional consensus of 1.5–2.0 (Chodorow-Reich, 2019; Suárez Serrato and Wingender, 2016; Nakamura and Steinsson, 2014).

Two channels drive these effects: direct stimulus of the construction sector and indirect demand spillovers. The stimulus pays contractors to rebuild roads and other public infrastructure, causing local government construction outlays to rise by 42%, bank construction and land-development loans by 11%, construction establishments by 4.9%, and construction earnings by 8.9%. But scaled by construction's relatively small share of the local economy, the direct reconstruction channel accounts for only about 23% of the establishment effect and 10% of the income effect. The remaining 77–90% flows through demand spillovers: rebuilt infrastructure supports private activity in sectors not directly impacted by Public Assistance, but for which the infrastructure repair is critical.

The high marginal returns to repaired infrastructure imply that local governments were not funding these repairs themselves. The reason, as is well documented, is that they face binding fiscal constraints in the wake of a disaster (Jerch et al., 2023). I test whether federal aid relaxes these constraints, and find that it does on every margin: outstanding debt falls by 15%, the effective property tax rate falls by 7.6%,

and municipal bond offering yields fall by 0.30 percentage points (Section 5). In addition to funding repairs that local governments could not finance themselves, federal aid stimulates recovery of the tax bases critical to local government revenues. Holding rates fixed, the increases in house prices, retail sales, and income would raise property tax revenue by 0.4%, sales tax by 1.8%, income tax by 2.6%, license tax by 3.5%, and total local tax revenue by roughly 0.5% per $100 of PA.

To translate the reduced-form effects into a welfare estimate, I specify and estimate a spatial-equilibrium model. The model is Rosen-Roback (Rosen, 1979; Roback, 1982) enriched with infrastructure as public (non-rival) capital that enters the production function and adds to the amenity value of a place as a public good, and with a local government optimally choosing its tax rate and debt issuance. This captures how federal aid stimulates local recovery, loosens local fiscal constraints, and allows me to distinguish between transfers among agents (e.g., higher rents paid by workers to landlords) and genuine welfare gains (e.g., higher productivity from restored public capital). I find a marginal value of $4.62 per federal dollar. Workers capture 60% of this through higher wages and amenities; landlords receive 36% as capitalized rent appreciation; the remainder is a reduction in deadweight loss as the local government is able to lower tax rates.

The remainder of the paper proceeds as follows. Section 2 provides institutional background on FEMA Public Assistance; Section 3 describes the data and identification strategy; Section 4 reports the causal effects on local economic outcomes; Section 5 turns to local government finance; Section 6 develops the spatial-equilibrium welfare model; and Section 7 concludes.

1.1. Literature Review

A substantial literature estimates the effects of disasters on local economic and financial conditions. The findings are hard to reconcile: some papers find positive effects on income, employment recovery and house prices (Roth Tran and Wilson, 2025; Belasen and Polachek, 2009; Deryugina et al., 2018), while others find negative effects (Strobl, 2011; Boustan et al., 2020; Hsiang and Jina, 2014). Often this gap is attributed to differences in disaster aid - which varies sharply across affected places - but this has never been directly demonstrated. Gallagher et al. (2023) use a triple-difference design to estimate FEMA Individual Assistance and find that household cash grants raise local employment and reduce credit card debt. Re-

latedly, Gallagher and Hartley (2024) document that local bank market structure shapes how much credit flows after disasters, with bank market share affecting the speed of county-level recovery. Erda (2026) uses Census plant microdata to document creative destruction and aggregate manufacturing productivity increases after floods, a micro-foundation for the aggregate effects I observe. I provide the first causal estimates of the effect of FEMA Public Assistance - the largest federal disaster aid program and the primary vehicle for public infrastructure repair - and demonstrate large positive effects across local income, employment, business activity, house prices, and public finance outcomes.

Numerous papers estimate the multipliers of fiscal stimulus. National fiscal expansions such as defense buildups yield multipliers of 0.6–1.0 (Ramey, 2011; Barro and Redlick, 2011); estimates from regional variation in defense procurement, ARRA stimulus, federal grants, and Medicaid cluster at 1.5–2.0 (Nakamura and Steinsson, 2014; Suárez Serrato and Wingender, 2016; Chodorow-Reich, 2019). My estimate - a gross income multiplier of roughly 9 - is much larger than most because the spending repairs a critical asset at a time when the returns to rebuilding destroyed capital are very high, consistent with Aschauer (1989). Relatedly, in normal contexts federal funds simply crowd out state or local spending rather than supplementing it (Knight, 2002; Gordon, 2004). Post-disaster federal aid is a notable exception: I find no offsetting reduction in local spending.

The reason that post-disaster aid does not displace local spending is that disasters sharply strain local government finances. Jerch et al. (2023) document that hurricanes reduce county tax revenue, raise expenditures, and elevate borrowing costs over the subsequent decade. Auh et al. (2022) find that disasters depress municipal bond returns, and Painter (2020) shows that climate-exposed counties pay higher underwriting fees on long-term municipal debt.[2] I show that federal aid reverses each of these margins: municipal outstanding debt is reduced, effective property tax rates are lowered, and municipal bond yields are compressed. Hence, federal disaster aid functions as insurance against shocks local governments cannot self-absorb, paying for repairs they could not otherwise afford and sparing them the fiscal strain of self-financing.[3]

[2]A broader municipal-bond literature documents that yields reflect liquidity and default risk premia (Schwert, 2017) and, increasingly, exposure to physical climate risk (Goldsmith-Pinkham et al., 2023).

[3]Consistent with classical work on federal fiscal constitutions and interstate risk sharing (As-

2. Institutional Background

When a natural disaster strikes, public infrastructure and private property are damaged. The latter receives protection from ex-ante insurance (homeowners, commercial, flood, etc.) or ex-post from FEMA programs such as Individual Assistance (IA).[4] The former - primarily damage to roads, bridges, utilities, and other public infrastructure - has minimal ex-ante insurance coverage.[5] Instead, almost all rebuilding is financed ex-post through the federal government's Public Assistance (PA) program.

PA works as follows. After a natural disaster occurs, officials assess and estimate the damage to public infrastructure. Within 30 days of the disaster, the Governor of the affected state or territory submits a request for PA. FEMA evaluates the need for PA, primarily by comparing infrastructure damage to statewide and county-wide thresholds of $1.89 and $4.72 per person, respectively (2025 dollars). These thresholds proxy for damage that is beyond the capacity of states or localities to repair without federal funding. In addition to the cutoffs, FEMA also considers localized impacts, recent prior disasters, and other factors that affect the local government's capacity to respond without federal help. The President then makes a declaration that activates PA in certain counties.

Once PA has been activated in a county, states and local governments can request funds for specific repair projects. Projects are then formulated with detailed scopes of work and cost estimates, reviewed and approved by FEMA. FEMA obligates funds to the state, which disburses them to the local applicant. The federal cost share is 75%, with state and local governments covering the remainder.[6] Regulatory deadlines mean that emergency work projects (debris removal and protective measures) must be completed within 6 months, while permanent infrastructure repairs can take up to 18 months, though extensions are common. Figure 2 shows that most projects are completed within 1 year of the disaster declaration. However, for large projects (measured by dollars obligated) it takes 3 years to complete 90% of emergency repairs, and 5 years for 90% of permanent work.

drubali et al., 1996; Persson and Tabellini, 1996; Deryugina, 2017).

[4] Despite both ex-ante and ex-post protections, the majority of household disaster damage in the US is uninsured (Kousky, 2019; Billings et al., 2022; Gruber and Solomon, 2026).

[5] Dixon et al. (2020) find that insurance proceeds cover only 22% of rebuilding costs for all PA projects from 2008 to 2018.

[6] The President can authorize a higher federal share, up to 100%, for catastrophic events.

PA is not the only federal program that responds to disasters. The National Flood Insurance Program (NFIP) pays claims to insured homeowners and businesses. The Small Business Administration (SBA) offers subsidized disaster loans to households and firms. FEMA's IA program provides grants directly to households for temporary housing and personal property losses. The Department of Housing and Urban Development allocates Community Development Block Grants for Disaster Recovery (CDBG-DR) to affected states, and the Federal Highway Administration reimburses states for interstate highway repairs through its Emergency Relief program. With the exception of the latter, these programs target private losses rather than public infrastructure. Since the object of interest in this paper is the causal effect of the marginal dollar of PA, the econometric methods will need to deal with the likely correlation between disaster severity and all these forms of federal assistance. This is discussed in detail in Section 3.3.

3. Data and Identification

3.1. Data

The analysis combines county-level damage assessments parsed from PA requests, project-level PA obligation records, and economic and financial outcome data from a variety of sources. Here I describe the construction of the treatment variable and instruments, then briefly summarize the outcome data. Appendix A provides full details on each source.

Infrastructure damage assessment. County-level infrastructure damage comes from FEMA Preliminary Damage Assessment (PDA) reports submitted by state governors to the President. These report estimated damage per capita in each county that is eligible for Public Assistance.

Public Assistance Spending. Cumulative PA spending per capita - the treatment variable - comes from OpenFEMA's *Public Assistance Funded Projects Details*. This dataset contains project-level records with obligation amounts and dates for every PA project since 2007. I aggregate projects to the county-disaster-year level, constructing cumulative federal PA dollars per capita obligated to county i in disaster d through calendar year t. The variable is zero in all pre-disaster periods and increases as FEMA disburses funds.

Sample construction. The analysis sample consists of county-disaster pairs where: (i) the county appears in a standard (non-expedited) PDA with positive assessed damage, (ii) the disaster affects at least two counties in a state. This yields 9,015 county-disaster pairs across 2,461 unique counties and 670 disasters.

Figure 1 illustrates the sample coverage. The analysis covers 670 standard PDA disasters in the middle of the severity distribution, accounting for 17% of all PA dollars. Catastrophic events - which account for 81% of PA spending - are excluded because FEMA waives formal damage assessment during expedited declarations.

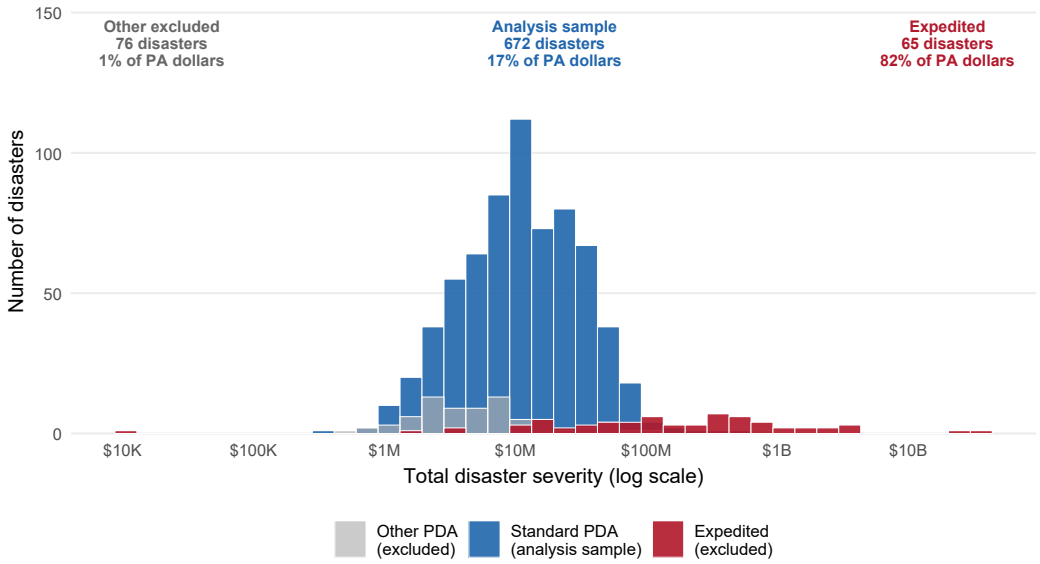


FIGURE 1. Disaster Severity and Sample Coverage

Notes: Distribution of 813 FEMA-declared disasters by total assessed infrastructure damage (PDA-assessed for standard declarations; PA obligations for expedited declarations). The analysis sample (blue) comprises 670 multi-county disasters with standard Preliminary Damage Assessments. Below-threshold disasters (gray) had no county exceeding the per capita damage indicator. Expedited declarations (red) - including Hurricanes Harvey, Irma, Maria, Ian, Ida, and Laura - are excluded because FEMA waives the PDA process and the damage estimates for catastrophic events.

Controls. The controls are designed so that the comparison holds two observations at the same level of damage, differing only in the amount of PA received. The damage controls are (a) the infrastructure damage estimates from the PA requests and (b) total damage including private property losses, which I measure with NOAA's Storm Events Database.

Data on spending in other disaster aid programs include: Individual Assistance

(IA) and NFIP flood insurance claims from OpenFEMA, SBA disaster loan approvals from FOIA data, CDBG-DR allocations from HUD financial reports, combined highway spending from the Government Finance Database and FHWA Emergency Relief program, and state-level private insured losses from NAIC. As I discuss below, the instrument I use only predicts PA spending, not any of these additional sources of disaster aid.

Outcome data.. I draw outcome variables from multiple sources, organized below by the results table in which they appear. Full variable definitions and source details are in Appendix A.

- **Table 3** (Income, Employment, Housing): county-level income from the Bureau of Economic Analysis CAINC1 dataset, local unemployment from the Bureau of Labor Statistics Local Area Unemployment Statistics, and county-level house price indices from the Federal Housing Finance Agency.
- **Table 4** (Establishments, Entrepreneurship): establishment and employment counts from Census County Business Patterns, new business applications from Census Business Formation Statistics (2005–2024), and sole-proprietor receipts from Census Nonemployer Statistics (1997–2022).
- **Table 5** (Population, Migration): county population from BEA CAINC1, and county-to-county migration flows from IRS Statistics of Income tax return data.
- **Table 6** (Reconstruction): local government construction expenditure from the Government Finance Database, construction and land-development loans from FDIC Call Reports, construction establishment counts from Census CBP, and construction-sector earnings from BEA CAINC5N.
- **Table 7** (Retail Activity): county-year total retail sales, counts of unique active participating stores, and counts of unique UPCs sold, aggregated from NielsenIQ Retail Scanner store-week-UPC transaction records.[7]
- **Table 8** (Local Government Finance): government revenue, expenditure, and debt from the Government Finance Database (Pierson et al., 2015), restricted to Census of Governments years, and municipal bond offering yields from SDC Platinum.

[7] The panel for these outcomes is restricted to 2006–2017 since the retailer sample was dramatically expanded in 2018 (see Appendix A.22).

3.2. Descriptive Statistics

Summary statistics are presented in Table 1. A few important patterns stand out.

First, the infrastructure damage in the median and even 75th percentile disaster is well insured by public assistance. For the median, against $16 of per capita infrastructure damage, public assistance provides $12 per capita (three quarters of which is paid for by the federal government, the remainder by state and local). For the 75th percentile disaster the damage of $41 per capita is exactly covered by public assistance. For such smaller disasters many sources of insurance - public and private - pay essentially nothing, and public assistance is by far the most important source of funding.

Second, the conclusion is starkly different for larger disasters. In the damage-weighted mean disaster, there is over $2,000 of infrastructure damage per capita, of which approximately a quarter is reimbursed via PA and CDBG-DR (the two primary infrastructure-oriented programs). The gap is due to differences between assessed and reimbursed damage (i.e. damage may be assessed relative to replacement value, whereas PA reimburses only to get infrastructure back to pre-disaster condition), some degree of private insurance, funding scarcity, or additional programs such as the Federal Highway Administration's Emergency Relief Program.[8]

Third, economic conditions improve after disasters. Comparing outcomes two years post-disaster to one year pre-disaster, the unemployment rate is lower, while per capita income, house prices, and the number of establishments are all higher. This counterintuitive finding - that natural disasters are beneficial to the local economy - aligns with Belasen and Polachek (2008, 2009); Groen et al. (2020); Roth Tran and Wilson (2025); Hornbeck and Keniston (2017). As conjectured there, and confirmed in this paper, natural disasters are themselves economically destructive; all the benefits come from the concomitant inflow of fiscal stimulus.

[8]The FHWA-ER program only has data available from 2020 onwards. In Appendix G, I show that for that sub-sample of disasters, while FHWA-ER does reimburse a non-trivial portion of large disaster damage, it is neither predicted by the instrument I use for PA nor does it change the primary estimates on the effect of PA when it is included as a control variable.

TABLE 1. Summary Statistics

	Median	Mean	Dmg-Wt. Mean	P25	P75
Panel A: Disaster Characteristics					
County population	19,778	83,013	25,789	8,552	47,573
Counties per disaster	19	24	24	11	33
Assessed damage/capita	$16	$61	$2,091	$7	$41
PA federal/capita	$9.1	$45.6	$205.3	$2.7	$30.9
PA state-local/capita	$3.0	$15.2	$68.4	$0.9	$10.3
PA projects per county	11	23	28	5	26
IA/capita	$0.0	$2.7	$6.4	$0.0	$0.0
NFIP claims/capita	$0.0	$6.2	$31.1	$0.0	$0.2
SBA disaster loans/capita	$0.0	$1.6	$4.7	$0.0	$0.0
CDBG-DR/capita	$0.0	$47.2	$265.3	$0.0	$0.0
Panel B: Pre-Disaster Conditions $(t-1)$					
Unemployment rate (%)	5.2	5.6	5.1	3.7	7.1
Per capita income	$41,725	$44,094	$44,201	$36,210	$49,021
House price index	214.4	287.2	229.1	160.3	319.5
Establishments	410	1,965	637	192	1,075
Panel C: Post-Disaster Conditions $(t+2)$					
Unemployment rate (%)	4.8	5.5	5.4	3.6	6.9
Per capita income	$43,475	$45,751	$46,778	$37,424	$51,032
House price index	224.1	300.4	242.4	165.3	333.7
Establishments	417	1,987	620	191	1,092

Notes: Summary statistics for economic and financial outcomes, pre- and post-disaster. The data run include 9,015 county-disasters from 2007–2024 for which a non-expedited PDA was requested for more than 2 counties in a state. Dollar amounts in 2020 dollars. Panel A reports existing county characteristics and details of post-disaster spending. Panels B and C show pre-disaster $(t-1)$ and post-disaster $(t+2)$ county-level economic and financial conditions.



FIGURE 2. Cumulative PA Obligation by Years After Declaration

Notes: Cumulative share of Public Assistance obligated by years elapsed since disaster declaration. Emergency work (Categories A–B: debris removal, emergency protective measures) is shown in red; permanent work (Categories C–G: roads, utilities, buildings, parks, water control) is shown in blue. Solid lines are project-weighted; dashed lines are dollar-weighted.

3.3. Identification Strategy

The object of interest is the causal impact of an extra dollar of public assistance on economic outcomes. Obviously, public assistance is not randomly assigned: larger disasters attract more public assistance and have worse economic outcomes. Controlling for damage, both to infrastructure and overall, partially corrects this. Nevertheless, endogeneity concerns remain. The initial damage assessment I condition on is preliminary and noisy; counties with damage that turns out to be higher than estimated will have worse economic outcomes and receive more public assistance.

To overcome this, I use an instrumental variable. Specifically, I instrument cumulative public assistance received with the initial damage assessments of all other counties within the state affected by the same disaster. This leave-one-out instrument is a proxy for the overall disaster being more or less severe. But, because I condition on each county's own damage assessment, the IV effectively compares two counties with the same damage assessment, one of which has neighbors who were severely damaged, the other of which has neighbors who were lightly damaged.

Formally, I instrument cumulative PA per capita with leave-one-out peer damage per capita, interacted with a post-declaration indicator, and estimate, for county i affected by disaster d at time t:

$$\text{First stage:} \quad \text{CumPA}_{idt} = \pi Z_{id} \cdot \mathbf{1}[t \geq t_d^*] + \mathbf{X}_{id}'\phi + \alpha_i + \delta_t + \nu_{idt} \tag{1}$$

$$\text{Second stage:} \quad y_{idt} = \beta \widehat{\text{CumPA}}_{idt} + \mathbf{X}_{id}'\gamma + \alpha_i + \delta_t + \varepsilon_{idt} \tag{2}$$

where α_i and δ_t are county and calendar year fixed effects, and $\mathbf{X}_{id}$ includes quadratic own-damage controls - FEMA PDA (public infrastructure severity) and NOAA Storm Events (total property damage including private losses). Z_{id} is the mean PDA-assessed damage per capita of all other counties in disaster d, excluding county i, and t_d^* is the declaration date of disaster d.

The instrumental relevance is statistically quite strong: the F-statistic is approximately 12 or higher.[9] The first stage is illustrated in Table 2.

[9] To be sure there are no problems related to weak instruments, in all cases I report Anderson-Rubin weak-instrument robust confidence intervals.

TABLE 2. First-Stage Estimates: LOO Peer Damage on Cumulative PA Per Capita

	Cumulative PA/capita
LOO peer damage/capita	0.11***
	(0.033)
County + Year FE	Yes
Damage controls	FEMA + Storm (quadratic)
KP F	11.6
Observations	82,467
Counties	2,544

Notes: First-stage regression results. The dependent variable is cumulative FEMA Public Assistance per capita ($/person), the independent variable is the leave-one-out measure of damage per capita in all affected counties except the focal, interacted with a post-disaster indicator. I include county and calendar year fixed effects and FEMA PDA and NOAA Storm Events quadratic own-damage controls. KP F is the Kleibergen-Paap cluster-robust first-stage F-statistic. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

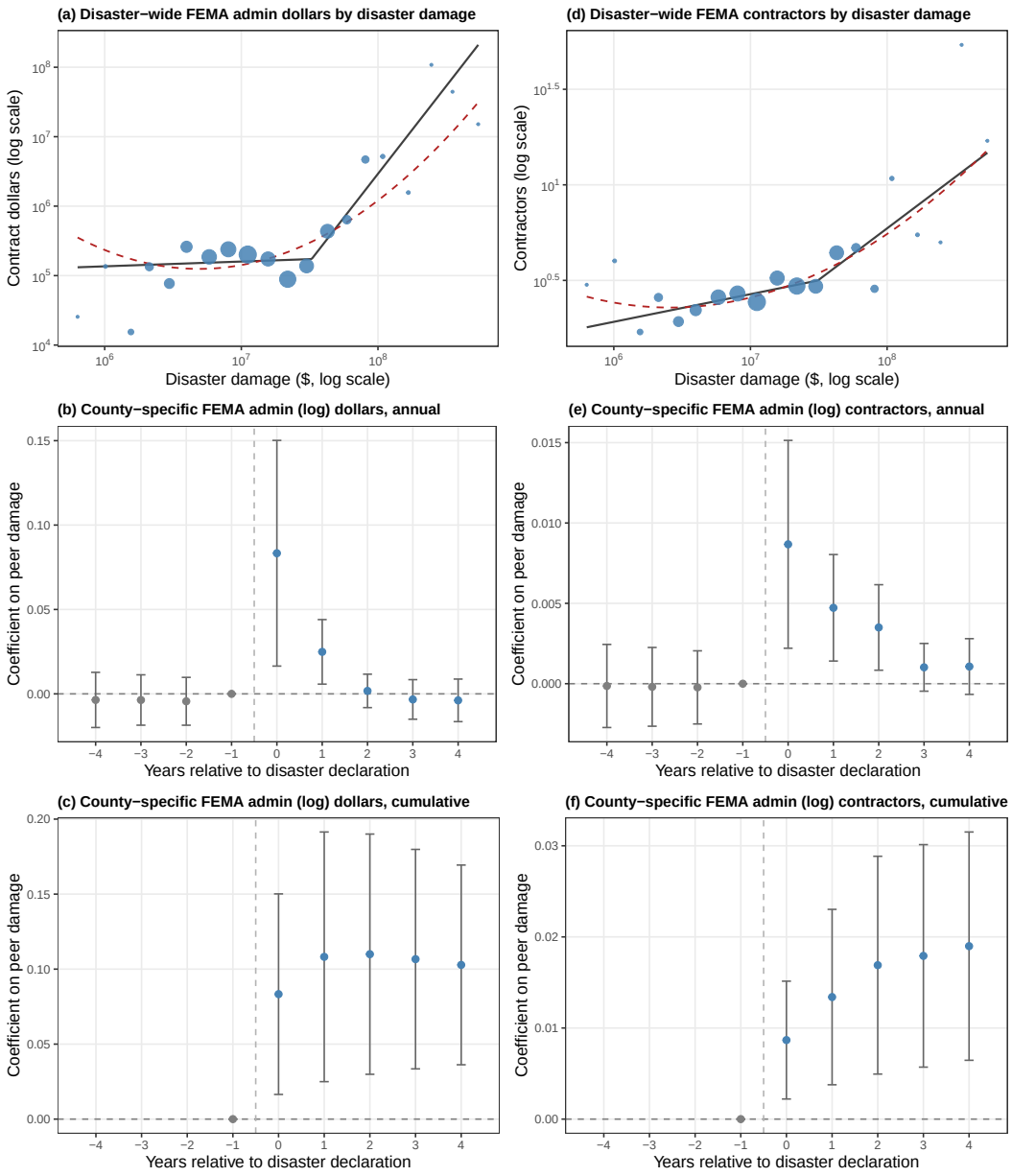


FIGURE 3. FEMA Administrative Mobilization

Notes: FEMA procurement records from USAspending, fiscal years 2007–2025 (Appendix A.27). Panels (a) and (d) plot, for each analysis-sample disaster, total contract obligations and distinct contractors linked to the disaster through disaster numbers in award descriptions, against total assessed damage; both axes are log scale, observations are grouped into twenty equal-width bins in log damage, and marker area is proportional to the number of disasters per bin. The solid line is a two-segment least-squares fit with an estimated break; the dashed line is a quadratic fit. The break is \$33 million of damage for dollars and \$31 million for contractors, with slopes of 0.07 below and 2.53 above for dollars and 0.14 and 0.54 for contractors. Panels (b), (c), (e), and (f) are event studies on the county-disaster-year panel. The dependent variable is the log of one plus contract dollars (contractors) both linked to the county's disaster and performed in the county; the independent variable is the leave-one-out measure of damage per capita in all affected counties except the focal (\$100/pc), interacted with event-time indicators ($k = -1$ reference period). All specifications include county and calendar year fixed effects and FEMA PDA and NOAA Storm Events quadratic own-damage controls. The cumulative panels plot cumulated post-declaration coefficients from the annual specifications, with confidence intervals from the joint cluster-robust covariance matrix. Because contracting specifics a disaster is essentially zero before its declaration, the pre-period estimates in the annual panels are mechanical rather than a placebo test. Bars show 95% confidence intervals based on standard errors clustered by county.

Conceptually, there are three clear reasons why two counties with similar damage but in disasters of different overall magnitude will receive differential FEMA assistance. First, FEMA establishes Joint Field Offices, deploys dedicated Preliminary Damage Assessment teams, and assigns local project officers only when a disaster is large enough to warrant these investments (Federal Emergency Management Agency, 2019; U.S. Government Accountability Office, 2023). Counties in larger disasters benefit from this administrative infrastructure - project officers are physically present to help local public works directors document damage and prepare project worksheets, whereas counties in smaller declared disasters interact with regional offices remotely and compete for limited staff attention.

Second, governors face near-zero marginal cost of adding counties to an existing declaration request. Counties with similar damage but whose neighbors are severely damaged are more likely to be granted public assistance as certain thresholds are state- or disaster-wide (McCarthy, 2014; Garrett and Sobel, 2003). Finally, Section 428 alternative procedures - which provide fixed-cost grants based on damage estimates rather than actual cost reimbursement - are predominantly used in large disasters and can result in higher obligations relative to assessed damage (Lindsay, 2023).

The common thread is that FEMA's presence in a county, holding the county's own damage fixed, scales with the disaster around it. Figure 3 documents this mobilization directly in FEMA's procurement records - the contracts the agency signs for technical assistance consultants, field office space, inspections, and logistics (Appendix A.27).[10] The top row shows the extensive margin across disasters: FEMA administrative dollars and contractors serving a disaster are convex in the disaster size. They are essentially flat in total damage up to approximately $33 million, then rise steeply. Hence, a county with given damage can receive much more assistance if other counties are sufficiently damaged so as to activate the broader FEMA apparatus.

The middle and bottom rows report an analogue to my IV: controlling for damage in the focal county, how the damage of other counties in the disaster predicts the

[10]These are FEMA's administrative purchases, not program dollars. Public Assistance grants are reported as federal financial assistance under Assistance Listing 97.036, not as procurement, and do not appear in contract records; recipients in the contract file are almost exclusively private firms (Appendix A.27).

level of FEMA administrative spending and contractors in the focal county. I find that a county whose peers were $100 per capita more damaged (approximately 0.87 standard deviations) has 9 percent higher FEMA administrative spend and 1% more contractors in the year of the disaster (middle row). This rises to over 10% and almost 2%, respectively, cumulatively four years after the disaster (bottom row). In Appendix B I corroborate this presence from outside the procurement data: transcripts of local governments' own public meetings show counties - controlling for damage - with harder-hit peers discussing FEMA's Public Assistance process far more after disasters.

3.4. Threats to Identification

Several concerns bear on an instrument of this kind. Three are specific to the leave-one-out design: that adjacent-county damage directly affects the focal county through economic linkages, that PA spending spills across county borders, and that the instrument proxies for generalized federal spending rather than PA specifically. Three are more general: political rather than scale-driven allocation within a disaster, measurement error in assessed damage, and contamination from repeated disasters. I address each in turn.

The first concern is that neighbor-county damage directly affects the focal county's economy, violating the exclusion restriction. The sign of this bias is ambiguous. Trade disruption, supply chain breakage, and reduced commuting demand would depress the focal county's outcomes, whereas spatial reallocation - businesses and labor fleeing damaged neighbors - would stimulate the focal economy. In Appendix J, I exclude adjacent counties from the IV construction and include adjacent county damage as controls. The primary results are qualitatively unchanged, and often stronger.

The second concern is that neighboring counties' PA spending spills over to the focal county. That is, the instrument generally correlates with local stimulus, and so the observed focal-county PA effect might actually be the sum of effects from focal and neighboring county PA. I test this directly by analyzing the effect of focal-county PA (instrumented as above) on adjacent counties *that were not affected by any disaster*. These neighbors have no disaster or PA spending of their own, and any economic effects would be pure spillovers. As shown in Appendix I, I find no economically or statistically significant spillovers.

The third concern is that the instrument is measuring generalized federal resource inflow rather than PA specifically. In Appendix G, I test whether the instrument predicts spending on other county-level federal disaster programs. It does not. I find that the instrument does not predict any additional federal spending from the NFIP, SBA, CDBG-DR, FEMA Individual Assistance, or state/federal highway spending. Moreover, controlling for these additional federal spending items does not meaningfully change the results from the primary analysis (see Appendix Table A5).

A further concern is that within-disaster allocation reflects political rather than scale-driven variation. Schneider and Kunze (2023) and Farkas and Kim (2025) benchmark PA allocation against hurricane wind speed and hydrological flood intensity respectively, and both find that political bias is concentrated in marginal events and vanishes for the most severe disasters. Farkas and Kim further show that the bias acts at the extensive margin of PDA inclusion rather than at the intensive margin of dollars allocated conditional on inclusion. My instrument exploits exactly the latter margin, and most of the PA in my sample flows to events large enough that their evidence suggests political allocation effects are negligible.

A related concern is that assessed damage is itself measured with error. Disaster damage is notoriously hard to quantify, and my design both conditions on own assessed damage and instruments with peer assessed damage, so a component of measurement error common to a disaster could bias the estimates. This matters when the measurement error in a county's own assessed damage correlates with its neighbors' damage: if assessors understate true damage by more in larger disasters, then among counties with the same recorded damage the ones with badly hit neighbors were in fact harder hit, and that unmeasured destruction drives both their Public Assistance and their economic outcomes - so peer damage would predict outcomes not through PA but through the focal county's own understated damage.

To deal with this concern, in Appendix K I rebuild both the instrument and the damage controls from measures of physical damage - flood and wind intensity constructed independently of FEMA - the same kinds of hazard measures used to benchmark disaster allocation (Schneider and Kunze, 2023; Farkas and Kim, 2025). The first stage becomes substantially stronger, and the results are largely unchanged. Because that comparison could still fail if the assessed and physical

measures err together, I go further and add disaster fixed effects, identifying the core results from variation across counties within the same disaster alone and showing the results remain robust (Appendix L).

Finally, the median county in my sample experiences four disasters over the panel, raising the concern that repeated treatment contaminates the comparison group or that pre-existing trends from earlier disasters bias the estimates. I address this in Appendix E. I restrict the sample to each county's first observed disaster, and separately to counties experiencing their first disaster in 5 or in 10 years. In all cases, the results get stronger: PA has, if anything, a larger effect once I remove any contamination from prior disasters.

4. Results

In this section, I analyze the impact of a marginal dollar of Public Assistance infrastructure repair on a range of economic and financial outcomes. There are some commonalities across all results.

First, I report OLS and IV results, as well as Anderson-Rubin CIs for the latter. Results are scaled to be per $100 of Public Assistance per capita, which is approximately double the mean amount in the sample. Where possible, corresponding event studies are reported in Appendix D. In general, the OLS results are sharply attenuated relative to the IV. This is because, in the cross-section, more damaged places have worse economic outcomes but also receive more public assistance.

I emphasize that throughout I flexibly control for the damage the disaster caused in the county, using both the FEMA PDA estimate for infrastructure damage and the Storm Events Database estimate for total damage. These FEMA PDA estimates are noisy, and to be sure that measurement error is not driving the results, in Appendix K I show that these controls, and the instrument, can be replaced with physically modeled flood and wind intensity constructed independently of FEMA's assessment without changing the results, and that they hold even when identified from variation across counties within the same disaster (Appendix L).

Moreover, county and year fixed effects capture time- and space-invariant unobservables. The comparison, therefore, is between two counties that were at similar levels of the outcome and received identically damaging storms. But, one of these

otherwise identical counties received more public assistance owing to its neighbors being hit harder (i.e. a larger overall disaster) such that FEMA mobilized more assistance and resources to help counties through the PA application and recovery process.

4.1. Income, Employment, Housing and the Fiscal Multiplier

I study the effect of the stimulus provided by infrastructure rebuilding on core indicators of economic health: local income, unemployment and house prices. Table 3 reports the results.

TABLE 3. Effects of FEMA Public Assistance on Income, Employment, and Housing

	Per Capita Inc. (1)	Total Inc. (2)	Unemp. Rate (3)	House Price Idx. (4)
Panel A: OLS				
\$100 cum. PA/capita	0.0019***	0.0011*	-0.024***	0.11
	(0.00069)	(0.00065)	(0.0086)	(0.30)
Panel B: IV				
\$100 cum. PA/capita	0.025***	0.033***	-0.39***	13***
	(0.0073)	(0.0087)	(0.093)	(3.7)
AR 95% CI	[0.0071, 0.041]	[0.012, 0.053]	[-0.71, -0.25]	[7.1, 22]
KP F	12	12	12	29
Outcome mean	\$23,600	\$2.8B	6.0%	251.7
Observations	77,199	77,199	77,667	65,816
Source	BEA CAINC1	BEA CAINC1	BLS LAUS	FHFA
County + year FE	Yes	Yes	Yes	Yes
Damage controls		FEMA + Storm (quadratic)		
Clustering	County	County	County	County

Notes: Estimates of the impact of additional PA per capita on income, employment and housing outcomes. Coefficients are scaled to reflect the effect of \$100 per capita in cumulative PA. The estimating equations are (1) and (2). Panel A reports OLS estimates. Panel B reports IV estimates. AR 95% CI denotes the Anderson-Rubin weak-instrument-robust confidence interval. KP F is the Kleibergen-Paap cluster-robust first-stage F-statistic. Data sources: per capita income and total income from BEA CAINC1; unemployment rate from BLS LAUS; house price index from FHFA. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I find that a marginal increase in infrastructure rebuilding through public assistance has substantial effects. Specifically, an extra \$100 of public assistance increases local per capita income by 2.5%, total income by 3.3%, lowers the unem-

ployment rate by 0.39 percentage points, and increases the house price index by 13 points. Scaled by the outcome means, these equate to an extra $1,050 of income per capita,[11] $92 million of total income in the county, a 6.5% lower unemployment rate, and a 5.2% increase in house prices.[12]

The ideal counterfactual is the effect of a disaster absent any aid. The literature does not isolate this cleanly, but I can compare the treatment effects of public assistance to the reduced-form effects of disasters. A disaster reduces income by 0.45%, reduces house prices by 2.5–5%, and raises unemployment by up to 4% (Strobl, 2011; Boustan et al., 2020; Indaco et al., 2021). My estimates show that the average amount of PA more than offsets the unconditional disaster effects. This is consistent with - and explains - the finding that the average presidentially declared disaster raises per capita income on net (Roth Tran and Wilson, 2025).

Fiscal Multiplier. The IV coefficient on per capita income implies that a dollar of cumulative public assistance per capita raises annual per capita income by about $9 (in 2010 dollars; $10.57 in current dollars). This income multiplier is four to six times standard local fiscal multiplier estimates of 1.5–2 (Nakamura and Steinsson, 2014; Suárez Serrato and Wingender, 2016; Chodorow-Reich, 2019). Unlike fiscal shocks in non-crisis times, the returns to rebuilding a road or bridge after a disaster are large: they enable economic activity and catalyze recovery. The income multiplier is a gross measure of economic activity; the welfare analysis in Section 6 converts the reduced-form responses into a net value of $4.62 per dollar after stripping out transfers between residents, landlords, and the local government.

4.2. Establishments and Entrepreneurship

Beyond raising incomes and house prices, public assistance pulls new firms into the affected economy. Table 4 reports the effects on four measures of firm activity: the total count of operating establishments, new business applications, sole-

[11] These income and economic activity gains are also visible in the local banking sector: Appendix N shows that an extra $100 per capita of PA raises county-level bank deposits by 3.0% and bank net income by 6.6%. Additionally, it lowers the nonperforming loan ratio by 16%, implying higher credit quality and less financial distress.

[12] Sub-state GDP measures (BEA CAGDP1/CAGDP2) are constructed by allocating state-level value-added to counties using industry wage and capital proxies, which makes them substantially noisier than the directly measured personal income series used here. The IV estimate on log county GDP is statistically null (+0.05%, $p = 0.96$, SE = 1.0pp), with a 95% CI wide enough to contain the implied output effect.

proprietor revenue, and the business application rate per 1,000 population.

An extra $100 per capita of public assistance increases the number of establishments by 2.4%, business applications by 8.3%, sole-proprietor revenue by 4.1%, and the business application rate by 0.67 per 1,000 population. Scaled by the outcome means, these equate to 57 additional establishments, 88 additional business applications, and an extra $13,300 in sole-proprietor revenue in the average county. Without aid, disasters move in the opposite direction: Indaco et al. (2021) find that Hurricane Sandy flooding reduced NYC establishment employment by 4%.

Some of this firm-entry response flows mechanically to construction firms as PA dollars finance the rebuilding of damaged infrastructure. In Section 4.4 I decompose the establishment effect into its direct and indirect channels: roughly 23% reflects direct entry of construction-sector firms, and the remaining 77% reflects indirect demand spillovers from the income gains in Section 4.1.

4.3. Population and Migration

Boustan et al. (2020), using a century of US county data, find that severe disasters raise out-migration by 1.5 percentage points and depress local population. To what extent does public assistance reverse this displacement? Table 5 reports the effects on county population and migration flows.

An extra $100 per capita of public assistance increases county population by 0.67%, the in-migration flow by 7.8%, and the out-migration flow by 3.7%.[13] Population is a stock; the migration flows are annual counts of tax returns (on average representing 1.7 people) moving into or out of the county, with the average county's inflow and outflow each around 2,500 per year.

The population response reconciles the total-income and per-capita-income estimates in Table 3: total income rises by 3.3%, per capita income by 2.5%, and the 0.8 percentage point difference is roughly the 0.67% population increase. PA's effect on local income operates through both channels - existing residents earn more, and new residents are drawn into the recovering economy. The migration and population responses persist for at least four years post-disaster (Figure A4 in

[13]Population is measured using the Census Small Area Income and Poverty Estimates (SAIPE). The result is stable across alternative data sources - BEA CAINC1 (+0.76%) and the CDC WONDER Compressed Mortality File denominator (+0.50%); see Table A17 in Appendix P.

TABLE 4. Effects of FEMA Public Assistance on Establishments and Entrepreneurship

	Establishments (1)	Bus. Apps. (2)	Sole-Prop. Revenue (3)	Bus. App. Rate (4)
Panel A: OLS				
$100 cum.	0.00018	0.00026	0.0019**	0.0031
PA/capita	(0.00031)	(0.0016)	(0.00076)	(0.013)
Panel B: IV				
$100 cum.	0.024***	0.083***	0.041***	0.67***
PA/capita	(0.0062)	(0.019)	(0.0095)	(0.15)
AR 95% CI	[0.013, 0.042]	[0.044, 0.13]	[0.024, 0.068]	[0.41, 1.2]
KP F	15	12	15	12
Outcome mean	2,381	1,065	$324,602	7.2
Observations	72,410	76,748	72,414	76,748
Source	Census CBP	Census BFS	Census NES	Census BFS
County + year FE	Yes	Yes	Yes	Yes
Damage controls	FEMA + Storm (quadratic)			
Clustering	County	County	County	County

Notes: Estimates of the impact of additional PA per capita on establishments and entrepreneurship outcomes. Coefficients are scaled to reflect the effect of $100 per capita in cumulative PA. The estimating equations are (1) and (2). Panel A reports OLS estimates. Panel B reports IV estimates. AR 95% CI denotes the Anderson-Rubin weak-instrument-robust confidence interval. KP F is the Kleibergen-Paap cluster-robust first-stage F-statistic. Data sources: establishments from Census CBP; business applications and the business application rate (per 1,000 population) from Census Business Formation Statistics (2005–2024); sole-proprietor revenue (in $1,000s, measured as nonemployer receipts) from Census Nonemployer Statistics (1997–2022). Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 5. Effects of FEMA Public Assistance on Population and Migration

	Population (1)	In-Migration Flow (2)	Out-Migration Flow (3)
Panel A: OLS			
$100 cum.	-0.00072**	0.0026**	-0.00022
PA/capita	(0.00032)	(0.0012)	(0.0011)
Panel B: IV			
$100 cum.	0.0067***	0.078***	0.037***
PA/capita	(0.0026)	(0.019)	(0.012)
AR 95% CI	[0.0018, 0.014]	[0.045, 0.14]	[0.011, 0.066]
KP F	13	15	15
Outcome mean	95,768	2,530	2,518
Observations	75,418	71,188	71,305
Source	Census SAIPE	IRS SOI	IRS SOI
County + year FE	Yes	Yes	Yes
Damage controls		FEMA + Storm (quadratic)	
Clustering	County	County	County

Notes: Estimates of the impact of additional PA per capita on population and migration outcomes. Coefficients are scaled to reflect the effect of $100 per capita in cumulative PA. The estimating equations are (1) and (2). Panel A reports OLS estimates. Panel B reports IV estimates. AR 95% CI denotes the Anderson-Rubin weak-instrument-robust confidence interval. KP F is the Kleibergen-Paap cluster-robust first-stage F-statistic. Data sources: population (a stock measure) from Census SAIPE (1997–2023); in-migration and out-migration flows are annual county-level tax-return counts of filers moving into and out of the county (each return represents approximately 1.7 persons) from IRS Statistics of Income. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D).

4.4. Reconstruction

Public Assistance directly funds the rebuilding of damaged infrastructure, so part of the income multiplier I document must operate through the construction sector: increased expenditure, employment and income. However, if a large proportion of the income gains comes from the directly stimulated construction industry and not from indirectly induced economic activity, the positive-externality welfare case for such stimulus would be weaker.

I analyze the impact of Public Assistance on the construction sector. Specifically, I report four reconstruction-sector outcomes: local government construction expenditure, the stock of construction and land-development loans on local bank balance sheets, the count of construction establishments, and total construction-sector earnings.

An extra $100 per capita in cumulative PA raises local government construction outlays by 42% - the direct consequence of PA reimbursements being spent on rebuilding public infrastructure. Banks operating in the affected county increase the stock of construction and land-development loans on their balance sheets by 11%, financing the private-side projects that follow disaster recovery. The number of construction establishments rises by 4.9% (extensive margin), and total construction earnings rise by 8.9% (intensive plus extensive margin combined).

Multiplying the construction-earnings change of 8.9% by the (damage-weighted) construction-income share of 3.6% implies that construction contributes about 0.32 percentage points of income growth. Compared to the total effect - 3.3 percentage points - construction contributes approximately 10%. The analogous calculation for establishments gives a larger share: new construction firms account for approximately 23% of the total.[14]

Construction is a real and important transmission mechanism for PA: it directly absorbs federal dollars, employs local labor, and crowds in private credit. But its reach extends beyond the sector itself - the remaining 77–90% of PA's income and establishment effects flow through demand spillovers from rebuilding activity to

[14] Full calculation details are in Appendix F.

TABLE 6. Effects of FEMA Public Assistance on the Construction Sector

	Gov. Constr. (1)	RE Loans (2)	Estab. (3)	Earnings (4)
Panel A: OLS				
$100 cum. PA/capita	0.020	0.0096***	0.0034***	0.0016
	(0.014)	(0.0035)	(0.00093)	(0.0016)
Panel B: IV				
$100 cum. PA/capita	0.42***	0.11***	0.049***	0.089***
	(0.15)	(0.039)	(0.013)	(0.025)
AR 95% CI	[0.20, 1.1]	[0.00075, 0.18]	[0.024, 0.082]	[0.024, 0.15]
KP F	9	13	15	10
Outcome mean	$11M	—	231	$228M
Observations	11,068	74,610	71,753	68,331
Source	CGF	FDIC Call	Census CBP	BEA CAINC5N
County + year FE	Yes	Yes	Yes	Yes
Damage controls		FEMA + Storm (quadratic)		
Clustering	County	County	County	County

Notes: Estimates of the impact of additional PA per capita on construction sector outcomes. Coefficients are scaled to reflect the effect of $100 per capita in cumulative PA. The estimating equations are (1) and (2). Panel A reports OLS estimates. Panel B reports IV estimates. AR 95% CI denotes the Anderson-Rubin weak-instrument-robust confidence interval. KP F is the Kleibergen-Paap cluster-robust first-stage F-statistic. Data sources: local government construction expenditure from Census of Governments Finance (census years 1992–2022); the stock of construction and land-development loans on the books of banks operating in the county from FDIC Call Reports (Schedule RC-C, allocated to counties via branch deposit shares); construction establishments (NAICS 23) from Census CBP; NAICS 23 earnings (compensation plus proprietors' income) from BEA CAINC5N (2001–2024). Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

stimulate the rest of the local economy.

4.5. Retail Activity

Income gains, if directly stimulatory of the local economy, should flow through to consumer spending. To measure this, I use the Nielsen Retail Scanner (2006–2017), a near-census of sales of food, beverages, and household and personal-care goods at participating grocery, drug, mass-merchandiser, and convenience retailers.[15] Table 7 reports the IV results for three county-year outcomes: total dollar sales of retail goods in the Nielsen Scanner data, the number of stores in operation, and the number of distinct products sold.

An extra $100 per capita of public assistance raises total sales by 10.7%, the number of stores by 3.2%, and the number of distinct products sold by 5.1%. Retail spending in the Nielsen sample is 1.7% of local personal income, so a 10.7% rise in retail spending against a 3.3% rise in income implies about 5 cents of additional spending per dollar of additional income at Nielsen-sampled stores. Because the Scanner covers roughly half of packaged-goods retail, the implied marginal propensity to consume packaged goods is near 11 cents per dollar - close to the 10-cent retail MPC Broda and Parker (2014) estimate from scanner data.

5. Local Government Finance

Disasters impose severe fiscal stress on local governments. Jerch et al. (2023) find that hurricanes raise municipal spending and debt while eroding revenue, and Auh et al. (2022) find that disaster-exposed municipalities face higher borrowing costs. The results in Section 4 demonstrate this: the marginal dollar of public assistance is not crowding out a local dollar; otherwise the treatment effects would be close to zero. That the local government cannot fund the marginal dollar for infrastructure repair itself - despite an income multiplier of roughly nine - speaks to the limits of its financial resources and the strain a disaster places on it. This section asks the fiscal corollary: beyond what it rebuilds, does PA also spare counties the fiscal strain they would otherwise experience?

[15] Access is through the Kilts Marketing Data Center at the University of Chicago Booth School of Business under an academic data-use agreement. The Kilts sample expanded sharply in 2018. To avoid reconciliation issues, I therefore restrict the panel to 2006–2017, when the retailer sample is stable within counties. See Appendix A.22 for details.

TABLE 7. Effects of FEMA Public Assistance on Local Retail Activity

	Retail $ (1)	Active Stores (2)	Unique UPCs (3)
Panel A: OLS			
$100 cum. PA/capita	0.010	0.0022	0.0037
	(0.0068)	(0.0030)	(0.0032)
Panel B: IV			
$100 cum. PA/capita	0.11***	0.032**	0.051**
	(0.039)	(0.015)	(0.020)
AR 95% CI	[0.052, 0.16]	[0.0035, 0.060]	[0.024, 0.095]
KP F	36	36	36
Outcome mean	$102M	14 stores	67K
Observations	38,681	38,681	38,681
Source	Nielsen RMS	Nielsen RMS	Nielsen RMS
County + year FE	Yes	Yes	Yes
Damage controls	FEMA + Storm (quadratic)		
Clustering	County	County	County

Notes: Estimates of the impact of additional PA per capita on local retail activity outcomes. Coefficients are scaled to reflect the effect of $100 per capita in cumulative PA. The estimating equations are (1) and (2). Panel A reports OLS estimates. Panel B reports IV estimates. AR 95% CI denotes the Anderson-Rubin weak-instrument-robust confidence interval. KP F is the Kleibergen-Paap cluster-robust first-stage F-statistic. Data sources: Nielsen Retail Scanner county-year aggregate (2006–2017), derived from store-week-UPC transaction records at participating grocery, drug, mass-merchandiser, and convenience retailers; access is governed by a data-use agreement with the Kilts Center at the University of Chicago Booth School of Business. The panel is restricted to 2006–2017 because Kilts expanded the retailer sample in 2018 (roughly a 45% one-time jump in store coverage), introducing within-county compositional shifts that fixed effects do not absorb; see Appendix A.22. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8 reports the effect of PA on four margins of local government finance. An extra $100 per capita of PA raises county capital outlays by 37%[16] and reduces outstanding debt by 15%. The rise in capital outlays answers the displacement question directly: PA adds to local public investment rather than replacing it - were PA merely substituting for local spending, capital outlays would not move. The debt reduction shows where substitution does occur. PA does not crowd out local *investment*; it relieves local *financing*. A county that receives PA rebuilds more and borrows less.

TABLE 8. Effects of FEMA Public Assistance on Local Government Finance

	Capital Outlay (1)	Debt Outst. (2)	Eff. Ptax Rate (3)	Muni Yield (4)
Panel A: OLS				
$100 cum. PA/capita	0.023***	0.000076	-0.0027	-0.0011
	(0.0074)	(0.011)	(0.0065)	(0.014)
Panel B: IV				
$100 cum. PA/capita	0.37***	-0.15*	-0.076***	-0.30*
	(0.12)	(0.079)	(0.029)	(0.15)
AR 95% CI	[0.21, 0.82]	[-0.41, 0.00086]	[-0.14, -0.020]	[-0.72, -0.039]
KP F	12	10	51	17
Outcome mean	$11M	$102M	1.51	$4
Observations	13,695	11,585	13,062	15,764
Source	CGF	CGF	CGF/FHFA	SDC Platinum
County + year FE	Yes	Yes	Yes	Yes
Damage controls		FEMA + Storm (quadratic)		
Clustering	County	County	County	County

Notes: Estimates of the impact of additional PA per capita on local government finance outcomes. Coefficients are scaled to reflect the effect of $100 per capita in cumulative PA. The estimating equations are (1) and (2). Panel A reports OLS estimates. Panel B reports IV estimates. AR 95% CI denotes the Anderson-Rubin weak-instrument-robust confidence interval. KP F is the Kleibergen-Paap cluster-robust first-stage F-statistic. The effective property tax rate is property tax revenue per capita divided by the FHFA house price index. Data sources: capital outlay, debt outstanding, and property tax revenue from Census of Governments Finance (Government Finance Database; county-only government units; census years 1992–2022); the offering yield is the par-weighted mean offering yield (%) on tax-exempt fixed-rate municipal bonds, restricted to county-years with rated bonds, from SDC Platinum (1990–2025); house price index from FHFA. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[16]The construction component of capital outlay - payments to contractors for new structures and improvements - is reported in Table 6 as part of the reconstruction channel.

Columns (3) and (4) turn from quantities to prices - the tax rate counties levy and the rate they pay to borrow. The effective property tax rate - property tax revenue per capita divided by the house price index - falls by 7.6%. PA broadens the tax base faster than it raises revenue: house values, incomes, and the number of establishments all grow (Section 4), so the county collects more revenue while levying a lower rate. Column (4) measures borrowing costs directly, from offering yields on newly issued municipal bonds. PA lowers the mean offering yield by 0.30 percentage points. This coheres with Auh et al. (2022), who find that counties receiving above-median federal aid per dollar of damage show no significant post-disaster decline in municipal bond returns, against a 1.2 percentage point drop where aid is absent. This confirms that federal aid neutralizes the municipal bond market's reaction to a disaster.

On every margin that disasters strain, PA pushes the other way: it funds public investment, reduces debt, lowers tax rates, and lowers borrowing costs. PA does not merely rebuild what the disaster destroyed - it spares counties the borrowing, the tax increases, and the deferred spending they would otherwise endure to recover on their own.

5.1. The Tax-Base Channel

The realized change in local tax revenue nets two opposing forces. PA expands the tax base - higher house values, incomes, and establishment counts (Section 4) - which raises revenue at a given rate. But counties also cut rates, as the 7.6% fall in the effective property tax rate shows. This subsection isolates the first force: the revenue effect of PA's tax-base expansion, holding rates fixed.

To do so, I directly estimate changes in the tax base. First, the IV estimates of the effect of Public Assistance on taxable bases (house prices, income and establishments) come from Tables 3 and 4. Second, the slope of the tax with respect to changes in the base is estimated via OLS. Their product is the effect of $100 of PA on total tax revenue, holding rates fixed, with delta-method standard errors. The results are in Table 9.

Holding tax rates fixed, PA's tax-base expansion raises revenue collected by every local tax: property tax by 0.4%, sales tax by 1.8%, income tax by 2.6%, license tax by 3.5%, and total revenue by 0.5% per $100 of Public Assistance. A broader base

TABLE 9. Effects of FEMA Public Assistance on Local Tax Revenue Through the Tax Base

Local tax	Tax base	PA → base (Stage 1)	Base → tax (Stage 2)	PA → tax (via base)	Baseline rev. per capita	Implied $ change
Panel A. County government						
Property tax	House prices	+5.2%	0.086***	+0.44%**	$462	+$2.05
			(0.024)	(0.18)		
Sales tax	Income	+2.5%	0.719***	+1.82%**	$161	+$2.93
			(0.239)	(0.80)		
Income tax	Income	+2.5%	1.028***	+2.60%**	$60	+$1.55
			(0.378)	(1.22)		
License tax	Establishments	+2.4%	1.447***	+3.46%***	$20	+$0.68
			(0.409)	(1.33)		
Panel B. All local governments within county						
Property tax	House prices	+5.2%	0.030	+0.16%	$1,355	+$2.11
			(0.040)	(0.21)		
Sales tax	Income	+2.5%	0.442***	+1.12%**	$252	+$2.82
			(0.116)	(0.44)		
Income tax	Income	+2.5%	0.962***	+2.43%**	$71	+$1.72
			(0.284)	(1.00)		
License tax	Establishments	+2.4%	1.053***	+2.52%***	$35	+$0.89
			(0.293)	(0.96)		

Notes: Estimates of the impact of Public Assistance on local-government tax bases. Stage 1 repeats the impact as estimated in Tables Tables 3 and 4. Stage 2 is the OLS elasticity of the tax revenue with respect to its base, estimated on Census of Governments census years with county and year fixed effects. The net effect of PA on the tax revenue, as mediated by the tax base, is computed as the product Stage 1 × Stage 2, with delta-method standard errors. Property tax uses a two-year house-price lag to account for assessment delay. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

mechanically yields more revenue. But counties do not hold rates fixed. The effective property tax rate falls 7.6%, more than the 5.2% rise in house values, so property tax revenue per capita actually declines by about 2.4%.

6. Welfare

To quantify the welfare impacts of Public Assistance, two additions to the reduced-form estimates in Sections 4 and 5 are necessary. First, transfers must be separated from real changes in surplus. For example, the 5.2% rise in house prices is partly a transfer from renters to landlords. Second, I need to locate the incidence of the surplus across workers, landlords, and the local government. To estimate the efficiency and incidence of PA, I write down and estimate a spatial-equilibrium model.

6.1. Model

The model is a Rosen-Roback spatial equilibrium with two non-standard ingredients. First, I add public capital (e.g. infrastructure). The economy is endowed with some public capital, but a disaster destroys it and PA restores some chosen amount. Public capital enters both the production function and worker utility directly as an amenity. Second, the local government chooses its tax rate and debt subject to a deadweight-loss cost of taxation. Standard models treat productivity and amenity as exogenous location characteristics while here both are functions of a public-capital stock that disasters destroy and federal aid (partially) restores.

I model a two-location economy: a disaster-affected county i and the rest of the country o, which is unaffected. A disaster destroys ΔK^g units of county i's public capital stock $\bar{K}_i^g$. The federal government provides PA_i dollars, which the county uses to restore public capital: $K_i^g = \bar{K}_i^g - \Delta K^g + \alpha \cdot PA_i$, where α is the restoration efficiency. I compare the post-disaster equilibrium under the observed PA_i to the counterfactual under alternative PA allocations.

Workers. A unit mass of workers is distributed across locations. Workers are mobile and choose where to live based on wages, housing costs and amenities. When PA makes county i more attractive, migration bids up rents until utility equalizes across locations. The migration elasticity therefore pins down how much PA-

induced surplus shows up as wages (kept by workers) versus rents (captured by landlords). Worker ν in location j receives indirect utility

$$V_j^\nu = w_j - r_j - \tau_j \frac{r_j}{\rho} + B_j + \epsilon_j^\nu = w_j - \left(1 + \frac{\tau_j}{\rho}\right) r_j + B_j + \epsilon_j^\nu, \tag{3}$$

where w_j is the wage, r_j is rent, τ_j is the property tax rate levied on the house price $P_j = r_j/\rho$ (with ρ the capitalization rate), B_j is a local amenity that depends on public capital ($B_j = b(K_j^g)$, with $b' > 0$), and ϵ_j^ν is an idiosyncratic location preference. I assume renters bear the full property tax.[17] I assume ϵ is i.i.d. Type I extreme value with scale parameter $\kappa > 0$, so location shares follow the logit:

$$\frac{N_i}{N} = \frac{\exp\left[(w_i - (1 + \tau_i/\rho)\, r_i + B_i)/\kappa\right]}{\sum_\ell \exp\left[(w_\ell - (1 + \tau_\ell/\rho)\, r_\ell + B_\ell)/\kappa\right]}. \tag{4}$$

The parameter κ governs the elasticity of migration: large κ means strong idiosyncratic attachment and sluggish migration. For a small county ($N_i/N \approx 0$), the migration semi-elasticity is $\partial \ln N_i / \partial B_i \approx 1/\kappa$.

Firms. Firms produce output using labor and public capital. They are not themselves welfare claimants - perfect competition drives profits to zero - but they are the channel through which restored public capital raises labor productivity and therefore wages. Competitive firms in county j produce output using labor N_j and public capital K_j^g:

$$Y_j = \left(K_j^g\right)^\beta N_j^{1-\beta}. \tag{5}$$

Public capital is a non-rival, non-excludable input: all firms benefit from the same roads, utilities, and public buildings. Firms take K_j^g as given and choose labor to maximize profits.[18]

[17] As is standard in spatial equilibrium with property taxation (Diamond, 2016; Fajgelbaum et al., 2019). The statutory pass-through pins down the accounting, not the economic incidence: the latter is governed by the housing supply elasticity η, which is already encoded in the IV-estimated rent and population responses and so does not need to be calibrated separately. Appendix Q backs out $\hat{\eta} \approx 0.16$ from the data.

[18] I omit private capital for tractability. If PA crowds in private investment - as the construction-establishment (+4.9%) and construction-earnings (+8.9%) results in Table 6 suggest - the welfare estimates here are conservative (Bom and Ligthart, 2014).

Housing. Landlords own the housing stock and capture rent appreciation as surplus. The supply elasticity η governs how much rent rises for a given demand shift and thus the share of PA-induced surplus that flows to landlords rather than to workers. Competitive landlords supply housing with an isoelastic supply function (Saiz, 2010):

$$H_j = \bar{H}_j \cdot r_j^{\eta}, \tag{6}$$

where $\bar{H}_j$ is a location-specific housing endowment and $\eta > 0$ is the supply elasticity. House prices are proportional to flow rents: $P_j = r_j/\rho$, where ρ is the capitalization rate. Landlord profits are rental income net of property taxes and construction costs:

$$\Pi_j^H = \left(1 - \frac{\tau_j}{\rho}\right) r_j \cdot N_j - C(N_j), \tag{7}$$

where $C(\cdot)$ is the cost function dual to (6). Landlords take r_j as given and choose N_j to maximize (7), yielding the first-order condition $(1 - \tau_j/\rho)\, r_j = C'(N_j)$: the after-tax rent on the marginal unit equals its marginal construction cost. By the envelope theorem, $d\Pi_j^H/dr_j = (1 - \tau_j/\rho)\, N_j$, so a marginal change in rent affects landlord profits only through inframarginal rent appreciation - the supply elasticity η summarizes the shape of $C(\cdot)$ that matters for welfare.

Local government. The local government collects property tax revenue, receives PA, and issues debt to balance its budget. Because taxation is distortionary, its choice of how to use a PA dollar - to lower the tax rate, to reduce borrowing, or to fund expenditure - determines how much of that dollar becomes efficiency gain rather than pure transfer. The local government's budget constraint is:

$$\tau_i \cdot \frac{r_i}{\rho} \cdot N_i + PA_i + D_i = G_i + (1 + i_b)\, D_{i,0}, \tag{8}$$

where G_i is total expenditure (including any locally financed restoration), i_b is the exogenous borrowing rate, $D_{i,0}$ is pre-existing debt, and D_i is new debt issued. The left-hand side lists revenue sources; the right-hand side lists obligations. PA enters the budget constraint directly, relaxing the government's financing need.[19]

Equilibrium. An equilibrium is a vector $(N_i, w_i, r_i, \tau_i, D_i)$ that satisfies labor and housing market clearing, the logit migration condition, the government's budget

[19] The endogenous tax rate creates a fiscal feedback loop: lower τ → in-migration → larger tax base → even lower τ. Appendix Q quantifies the amplification.

constraint, and the government's optimal choice of tax rate and debt (minimizing distortion plus debt service subject to the budget). Since county i is small relative to the rest of the country, I treat the outside option as fixed. Under $\tau_i < \rho$ - which holds for all US counties - the system has a unique solution; Appendix Q states the conditions formally and proves existence.

6.2. Welfare

PA's direct effects - higher wages from restored infrastructure, better amenity, and lower property tax rates - raise the county's location value and attract migration. In general equilibrium, migration compresses wages, raises rents, and expands the tax base; these forces are embedded in the reduced-form responses estimated in Sections 4 and 5 and stated formally in Appendix Q.

Public Assistance generates welfare for three groups: workers, through productivity (higher wages) and the amenity of restored public capital; landlords, through additional property tax base from new residents; and the local government, through lower DWL, debt service, and borrowing costs. Rent and property-tax transfers between groups net out:

$$\frac{d\mathcal{W}}{dPA} = \overbrace{\underbrace{N_i \frac{dw_i}{dPA}}_{\text{wages}} + \underbrace{N_i \frac{dB_i}{dPA}}_{\text{amenity}}}^{\text{worker welfare}} + \overbrace{\underbrace{\frac{\tau_i r_i}{\rho} \frac{dN_i}{dPA}}_{\substack{\text{tax base from} \\ \text{new residents}}}}^{\text{landlord welfare}} \tag{9}$$

$$+ \overbrace{\underbrace{-\frac{\partial \text{DWL}}{\partial \tau} \frac{d\tau_i}{dPA}}_{\substack{\text{DWL} \\ \text{reduction}}} \underbrace{-i_b \frac{dD_i}{dPA}}_{\substack{\text{debt service} \\ \text{savings}}} \underbrace{-D_i \frac{di_b}{dPA}}_{\substack{\text{borrowing cost} \\ \text{reduction}}}}^{\text{fiscal welfare}} - \text{MCPF}.$$

The last term, the marginal cost of public funds, is the federal cost of PA: raising \$1 imposes a deadweight loss on taxpayers. I use MCPF = 1.30 as the baseline (Feldstein, 1999), with sensitivity over the range 1.0–1.5.[20]

[20] Feldstein (1999) estimates $\lambda \approx 0.30$ for the US income tax. Ballard et al. (1985) report a range of 1.17–1.56 depending on the tax instrument. Setting MCPF = 1 recovers the formula under lump-sum federal financing.

6.3. Parameters and calibration

The welfare formula requires various ingredients, summarized in Table 10: causal responses estimated in prior sections (migration, house prices, tax rates, debt, borrowing costs), and calibrated parameters from prior sections or the literature (e.g., migration elasticity, capitalization rate, tax base elasticity, MCPF).

Given these inputs, Table 11 reports the decomposition of the welfare value of Public Assistance at these central parameter values. The gross MVPA is \$4.62 per dollar of PA: workers capture 60%, landlords 36%, and the local government 3%.

Worker surplus. Workers' welfare in equation (9) is computed from the migration response - $N_i \kappa d \ln N_i / dPA$ - which is a sufficient statistic for workers' net valuation of PA's effects (wages, amenity, tax bills, rents). Workers gain \$2.80, or 60% of the gross value - the bulk of the incidence. Public Assistance raises worker surplus through the direct amenity value of restored public capital, the productivity gain that workers share via higher wages, and lower property tax bills.

Landlord surplus. Landlords' welfare is the change in property profit. Property owners gain \$1.68, or 36%. Rent appreciation on existing units net of property tax contributes \$0.85; the tax rate windfall (PA reduces the effective tax rate by 7.6%, so landlords retain more of each rent dollar) adds \$0.77; property tax revenue from new residents adds \$0.07. The landlord share reflects inelastic short-run housing supply: house prices rise 4.4% while population grows only 0.67%, and building permits show no significant response.

Fiscal surplus. The fiscal surplus is \$0.14 (3% of total welfare). Reduced borrowing costs contribute \$0.08: the 0.30pp yield decline lowers annual interest on the debt stock. Debt service savings from the 15% debt reduction add \$0.05. The deadweight loss reduction from lower property taxes is \$0.01 - negligible because at $\tau = 1.72\%$, the distortion is small. The local government's lowering of taxes as its fiscal stress is eased operates indirectly: PA lowers tax rates, which attracts residents, which expands the tax base, which allows further tax reductions. This feedback is embedded in the IV estimates.[21]

[21] At $\tau/\rho \approx 0.34$, the fiscal feedback amplifies the population response by roughly 1.6%; see Appendix Q for the formal comparative statics.

TABLE 10. Inputs to the Welfare Formula

Description	Object	Value	Source	Type
IV estimates (from this paper)				
Migration response	$d \ln N / dPA$	+0.67%	Table 5	Estimated
House price response	$d \ln r / dPA$	+13 HPI pts	Table 3, via ρ	Estimated
Tax rate response	$d \ln \tau / dPA$	−7.6%	Table 8	Estimated
Debt response	$d \ln D / dPA$	−15%	Table 8	Estimated
Borrowing cost response	di_b / dPA	−0.30pp	Table 8, rated issuers	Estimated
Sample means (from data)				
County population	N_i	25,222	Median county population	Data
Home value	P_i	\$146,000	Zillow ZHVI, disaster-exposed	Data
Property tax rate	τ_i	1.72%	All-within-county ptax / P	Data
Borrowing rate	i_b	4.6%	GFD interest/debt ratio	Data
Outstanding debt	D_i	\$2,710/pc	All-within-county debt	Data
External parameters				
Migration sensitivity	κ	\$41,600	Diamond (2016)	Literature
Capitalization rate	ρ	5%	National price-to-rent ≈20	Literature
Tax base elasticity	ε	1.0	Property tax base wrt τ	Literature
Marginal cost of public funds	MCPF	1.30	Feldstein (1999)	Literature

Notes: Parameter inputs to the welfare model calibration. κ is calibrated from Diamond (2016), who estimates logit coefficients on log wages of 1.27 (college) and 0.56 (non-college). Using a pooled average $\gamma = 0.9$ and matching $\kappa = \bar{w}/\gamma$ yields $\kappa \approx \$41{,}600$. The effective property tax rate $\tau = 1.72\%$ is all-property tax revenue per home divided by the median home value; the all-within measure is used because school districts, municipalities, and special districts levy the majority of local property taxes. In the welfare formula the home value P and rent $r = \rho P$ are expressed per capita - dividing by the sample-mean household size of 2.47 - so that they are commensurate with the per-capita PA, income, and debt quantities.

TABLE 11. Welfare Decomposition: Marginal Value per PA Dollar

Component	Value ($/$1 PA)	Share
Worker surplus	**$2.80**	**60%**
$= N \cdot \kappa \cdot d \ln N / dPA$		
Landlord surplus	**$1.68**	**36%**
Rent appreciation (net of tax)	$0.85	
Tax revenue from new residents	$0.07	
Tax rate relief on existing units	$0.77	
Fiscal surplus	**$0.14**	**3%**
DWL reduction	$0.01	
Debt service savings (less debt)	$0.05	
Borrowing cost reduction (lower yield)	$0.08	
MVPA (gross value per $1 PA)	**$4.62**	**100%**

Notes: Results of the welfare calibration. Decomposition of worker, landlord and fiscal surplus is according to equation (9). For sensitivity of the welfare estimates to changing input parameters, see Appendix Q.

Sensitivity. The gross MVPA ranges from \$2.98 to \$7.39 across all parameter combinations ($\gamma \in [0.5, 1.5]$, $\rho \in [3\%, 7\%]$, $\varepsilon \in [0.5, 2.0]$); see Appendix Q for full sensitivity tables. The result is most sensitive to κ (which governs how much welfare accrues to inframarginal residents who benefit without migrating) and ρ (which converts HPI appreciation into landlord rental income).

7. Conclusion

When natural catastrophes destroy infrastructure, the economy of an entire region can be inhibited. I estimate the causal effect of federal infrastructure repair on local economic recovery. Across a wide range of outcomes - income, employment, house prices, entrepreneurship - repaired infrastructure has a dramatic impact. This implies that little or no rebuilding would have occurred without federal aid, which is striking given its large returns. I show that local governments are severely constrained by disasters and, in fact, a primary effect of federal aid is to ease those constraints: outstanding debt, tax rates and municipal bond yields all fall, while the revenue bases on which local tax is levied expand. The estimates support a view of federal infrastructure repair as insurance against shocks that overwhelm local fiscal capacity.

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Appendix A. Data Sources and Construction

This appendix documents each data source, the cleaning decisions applied, and the resulting sample sizes.

A.1. Preliminary Damage Assessment Reports

I parse 855 FEMA Preliminary Damage Assessments. Each PDA is a governor's request for a major disaster declaration for all affected counties in their state. I extract county names, damage amounts and whether or not PA was authorized for each requested county.

I exclude PDAs for 65 expedited declarations where FEMA waived the PDA. These catastrophic events - including Hurricanes Harvey, Irma, Maria, Ian, Ida, and Laura - account for $93.7 billion in PA obligations (81% of all PA). I also exclude biological incidents (e.g., COVID-19 declarations).

A.2. FEMA Public Assistance Obligations

PA obligation data come from OpenFEMA's *Public Assistance Funded Projects Details* endpoint, which contains project-level records with obligation amounts and dates. I aggregate to the county-disaster-year level to construct cumulative PA per capita: the treatment variable equals zero in all pre-disaster periods and increases as FEMA disburses funds. Statewide projects are excluded, as they cannot be attributed to specific counties.

A.3. Individual Assistance

IA per capita comes from OpenFEMA's Individuals and Households Program endpoint, aggregated to county-disaster totals. Only 8% of county-disasters have nonzero IA, reflecting that most declarations in the sample are PA-only.

A.4. NOAA Storm Events

Storm damage comes from NOAA's Storm Events Database, filtered to county-level records. I match storm events to FEMA disasters by county and a ±2-month window around the declaration date. The 56% match rate reflects that many smaller

disasters do not generate NOAA damage estimates, or that damage is recorded at the forecast zone level rather than the county level.

A.5. NFIP Claims

NFIP claims come from OpenFEMA's aggregated county claims file, summed by disaster and county.

A.6. SBA Disaster Loans

SBA disaster loan approvals come from FOIA requests covering FY2000–2022. Source formats vary across fiscal years. I match loans to FEMA disasters by county name and disaster number.

A.7. CDBG-DR

CDBG-DR allocations come from HUD financial reports at the state level. I allocate to counties proportional to assessed PDA damage within each state-disaster. Coverage is 20% of county-disasters, concentrated in larger events.

A.8. BEA County Personal Income

County-level personal income and population come from BEA CAINC1 (1969–2024). All dollar amounts are in current dollars; year fixed effects absorb common deflation.

A.9. BLS Unemployment

County unemployment rates come from BLS Local Area Unemployment Statistics, filtered to annual averages.

A.10. FHFA House Price Index

County-level house price indices come from the FHFA all-transactions index, based on repeat-sales of properties with Fannie Mae or Freddie Mac mortgages.

A.11. Census County Business Patterns

Establishment and employment counts come from annual CBP files (2000–2022), filtered to the all-industry total. Construction-sector outcomes use the NAICS 23

subset.

A.12. Census Business Formation Statistics

County-level new business applications come from the Census BFS program (2005–2024), which captures applications for an Employer Identification Number likely to result in a payroll business.

A.13. Census Nonemployer Statistics

Sole-proprietor establishment counts and gross receipts come from Census NES (1997–2022), covering establishments with no paid employees.

A.14. Census SAIPE

Poverty rates and median household income come from the Census Small Area Income and Poverty Estimates program (1997–2023).

A.15. IRS Migration Data

County-to-county migration flows come from IRS SOI tax return data (2005–2022). I extract total inflows and outflows for each county-year.

A.16. BEA Construction-Sector Earnings

Construction-sector earnings come from BEA CAINC5N (NAICS 23). Construction establishment and employment counts come from CBP filtered to NAICS 23.

A.17. Government Finance Database

Local government finance data come from the Government Finance Database (Pierson et al., 2015). I restrict to Census of Governments years (1992, 1997, 2002, 2007, 2012, 2017, 2022). I produce two aggregations: county government only and all governments within the county (summing across school districts, special districts, and municipalities).

A.18. ASPEP

Government employment and payroll come from Census ASPEP, restricted to the same census years as the GFD. Payroll is reported as a March monthly equivalent;

I annualize by multiplying by 12. I produce county-only and all-within-county aggregations, grouped by government function (public works, safety, health, administration).

A.19. SDC Platinum Municipal Bonds

Municipal bond offering yields come from SDC Platinum's US Municipal New Issues database (1990–2025). I filter to tax-exempt, fixed-rate, publicly offered bonds with offering yields between 0% and 15%.[22] I match bonds to counties using issuer county name, CUSIP prefix, and issuer name parsing, yielding approximately 190,000 matched bonds across 2,833 counties. I aggregate to county-year panels computing par-weighted offering yields, Treasury spreads, and bond characteristics (maturity, insurance status, credit rating).

A.20. FDIC Summary of Deposits

County-level bank deposits come from the FDIC Summary of Deposits (1994–2023), a branch-level annual census of all FDIC-insured institutions reporting deposits by office as of June 30 each year. I aggregate branch deposits to the county-year level.

A.21. FDIC Call Reports

Bank-level Call Reports (1994–2023) provide quarterly balance sheet and income statement data for every FDIC-insured commercial bank. I use the March filing of each year and extract total loans, construction and land-development loans, net income, and noncurrent loans (90+ days past due or nonaccrual). Because Call Reports are bank-level rather than branch-level, I allocate each bank's totals to counties in proportion to its branch deposit shares from the Summary of Deposits, following Gilje et al. (2016).

A.22. Nielsen Retail Scanner

Retail activity comes from the NielsenIQ Retail Scanner dataset. The raw data are store-week-UPC transaction records at participating retailers. I aggregate to

[22] SDC fields occasionally contain dollar prices rather than percentage yields; values above 20 are excluded.

the county-year level and compute total dollar sales, total unit sales, the count of unique participating stores, and the count of unique UPCs sold.

I restrict the analysis panel to 2006–2017. This is because in 2018 the panel expanded the participating-retailer roster: the nationwide count of active stores jumped roughly 45% and total measured retail dollars rose about 33% in a single year.

A.23. County Adjacency

County adjacency relationships come from the NBER 2010 county adjacency file, used to construct the non-adjacent instrument variant and neighbor sets for spillover tests.

A.24. NAIC Private Insured Losses

State-level private insured losses come from NAIC annual statutory filings, covering homeowners, commercial property, fire, and allied lines (2000–2022). Losses are aggregated to the state-year level and merged to the panel via state FIPS codes. These data enter the analysis only as a falsification and control variable in Appendix G: the instrument marginally predicts private losses but controlling for them changes PA coefficients by at most 3%.

A.25. LocalView Public Meetings

Local government meeting transcripts come from the LocalView database (Barari and Simko, 2023), which collects YouTube-captured public meetings of city councils, county boards, and other local bodies - roughly 150,000 meetings with usable captions over 2010–2023, from about 1,000 places nationwide. I map places to counties, locate every FEMA mention in the captions, and classify its context from the surrounding text; the resulting county-month mention rates underlie Appendix B.

A.26. FEMA Staff Deployments

Individual FEMA staff deployment records for fiscal years 2016–2023 come from the Department of Homeland Security's Office of Homeland Security Statistics: roughly 190,000 deployments, each keyed to a disaster declaration with on-site arrival and departure dates. The records are state-level and contain no occupation

field, so they measure total FEMA staffing per disaster rather than Public Assistance program staff in particular counties.

A.27. FEMA Procurement Records

FEMA's own contract spending comes from the federal procurement system via USAspending: roughly 210,000 transactions totaling $39 billion over fiscal years 2007–2025. These are contracts FEMA signs with private firms for its operations - technical assistance consultants, field office space, inspections, logistics - and are distinct from assistance grants. Public Assistance dollars cannot appear in these records: federal grants are reported as financial assistance, separately from procurement, and PA obligations instead appear in USAspending's assistance files under Assistance Listing 97.036 (Disaster Grants - Public Assistance), with state governments as recipients - $9.5 billion in fiscal year 2018 alone. The procurement file confirms the separation from its own side: recipients with government names hold 0.4 percent of contract dollars, and total contract obligations are an order of magnitude smaller than PA obligations over the same period ($39 billion against $276 billion). I link contracts to disasters through disaster numbers stated in award descriptions, which cover roughly a third of contract dollars, and to counties through each contract's place of performance, which covers 96 percent of transactions.

Appendix B. FEMA Mobilization

The identification strategy rests on FEMA mobilizing administrative capacity with disaster scale, and on that capacity reaching individual counties. This appendix documents both from sources outside the grants data.

The primary evidence comes from local governments' own public meetings. The LocalView database (Barari and Simko, 2023) collects roughly 150,000 YouTube-captured city council and county board meetings with caption transcripts between 2010 and 2023 (Appendix A.25). I locate every FEMA mention in these transcripts and classify its context from the surrounding text (±300 characters): mentions in Public Assistance process vocabulary - project worksheets, reimbursement, obligations, cost shares, damage assessment, debris removal - and mentions indicating that FEMA staff are engaging the local government directly ("met with FEMA,"

"FEMA representative"). I aggregate to mention rates per captioned meeting at the county-month level and estimate the first-stage design at this higher frequency: peer damage interacted with an indicator for the two quarters following the declaration, with county and year-month fixed effects, the standard own-damage controls, and a placebo window covering quarters −4 to −2.

Table A1 reports the results. An additional $100 per capita of peer damage raises discussion of the Public Assistance process by 0.051 mentions per meeting (p = 0.029 clustered by county, 0.022 by disaster) and mentions of FEMA staff engagement by 0.029 (p = 0.019; 0.012) during the two quarters after the declaration - increases of 92% and 60% relative to the sample means. Holding own damage fixed, county boards in larger disasters spend roughly twice as much meeting time on FEMA's grant process, exactly when applications are being formulated. The placebo window is insignificant for both outcomes. Measuring event time from the incident start instead of the declaration date gives similar results, with the staff-engagement effect strengthening (p = 0.005) and a somewhat larger, still insignificant, pre-window coefficient. One coverage caveat: LocalView counties are places whose governments broadcast meetings on YouTube, which skews urban - mean PA in this subsample is $19 per capita against $48 in the full panel.

FEMA's own deployment records tell the same story at the disaster level. Using individual deployment records for fiscal years 2016–2023 (Appendix A.26), I construct cumulative person-days deployed to each county's disaster - the staffing analogue of cumulative PA per capita, zero before the declaration and accumulating as staff arrive - and estimate the first-stage specification (eq. (1)) in event-study form with staffing in place of PA. The coefficients are positive at every post-declaration horizon and statistically significant at horizons two through four (p = 0.048, 0.030, 0.017; Figure A1). Because staffing is recorded at the disaster level, this evidence identifies from across-disaster variation: it shows the operation surrounding a county scaling with the instrument, conditional on own damage, not staff assigned to particular counties. Two further limitations are worth stating. The records begin in fiscal year 2016, and post-2016 declarations have had fewer years for assistance to accumulate - the PA first stage on this subsample is 0.074 (p = 0.049), versus 0.11 in the full sample - so the staffing test inherits a low power ceiling. And total deployments scale less than proportionally with assessed damage (elasticity of roughly 0.4), so the operation around a fixed-damage county

TABLE A1. FEMA in the Room: Local Public Meetings After a Declaration

	PA-process context (1)	FEMA staff present (2)
Peer damage ($100/pc) × quarters 0–1	0.0508**	0.0289**
	(0.0232)	(0.0123)
	[0.022]	[0.012]
Peer damage ($100/pc) × quarters −4 to −2	0.0136	0.0092
	(0.0120)	(0.0120)
Mean of outcome	0.055	0.048
Effect at mean, quarters 0–1	+93%	+61%
Observations	16,918	16,918
County FE	Yes	Yes
Year-month FE	Yes	Yes
Damage controls	Yes	Yes

Notes: County-disaster-month panel built from local government public meetings captured on YouTube (Barari and Simko, 2023), merged to the analysis sample of county-disaster pairs. The dependent variables count, per captioned meeting in the county-month, FEMA mentions whose surrounding text (±300 characters) contains Public Assistance process vocabulary (column 1: project worksheets, reimbursement, obligation, cost share, damage assessment, debris removal) or indicates FEMA staff engaging directly with the local government (column 2: "met with FEMA," "FEMA representative," and similar). The regressor is leave-one-out peer damage per capita (in $100/pc), interacted with an indicator for the two quarters following the disaster declaration; the second row interacts it with quarters −4 to −2 as a placebo window. All specifications include FEMA PDA and NOAA Storm Events quadratic own-damage controls and Individual Assistance per capita. Standard errors clustered by county in parentheses; p-values clustered by disaster in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

grows in absolute terms while staffing per dollar of damage falls.[23]

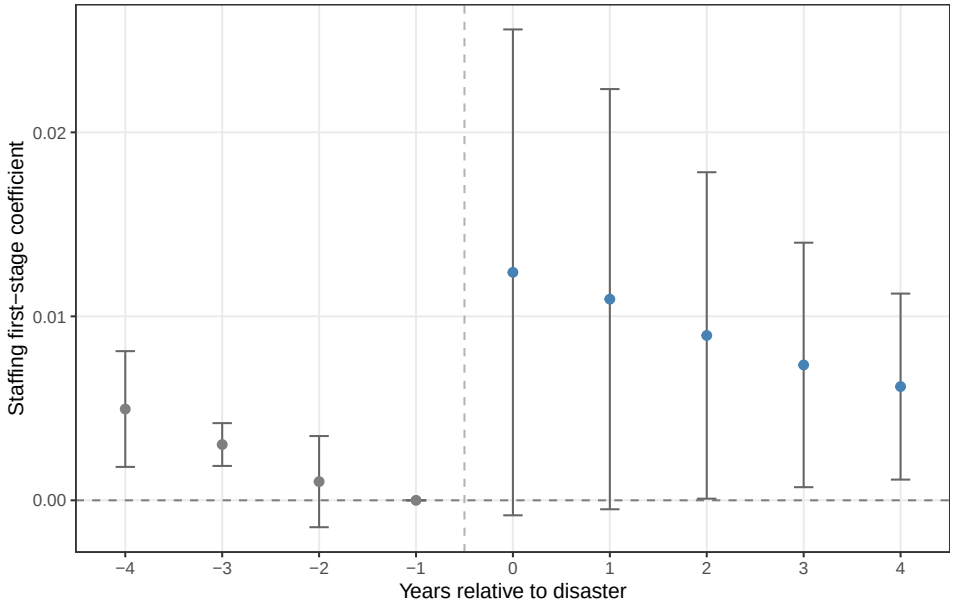


FIGURE A1. Staffing First-Stage Event Study

Notes: Event study of the first-stage specification (eq. (1)) with log(1 + cumulative FEMA person-days) deployed to the county's disaster as the dependent variable, in place of cumulative PA per capita. Staffing is measured from individual FEMA deployment records (Appendix A.26); the sample is restricted to disasters declared in 2016 or later. The independent variable is the leave-one-out measure of damage per capita in all affected counties except the focal, interacted with event-time indicators ($k = -1$ reference period). All specifications include county and calendar year fixed effects and FEMA PDA and NOAA Storm Events quadratic own-damage controls. Bars show 95% confidence intervals based on standard errors clustered by disaster.

Appendix C. Population-Weighted Estimates

The main tables report unweighted IV estimates, which identify the effect for the average county-disaster pair (median population approximately 25,000). Table A2 reports population-weighted estimates for all outcomes, which shift the local average treatment effect toward large, urban counties. The population-weighted first stage is substantially stronger (KP $F = 48$ vs. 12), but the two specifications identify different complier populations. Income and unemployment effects are larger;

[23] No deployment in the data predates its disaster's declaration year, so cumulative staffing is identically zero in the pre-period; the two nonzero pre-period estimates in Figure A1 reflect fixed-effect composition in the stacked panel rather than actual pre-declaration staffing, and are small relative to the post-declaration response.

establishment and public finance effects are attenuated, consistent with the reconstruction channel being relatively more important for smaller communities.

Appendix D. Reduced-Form Event Studies

The following figures plot IV-scaled event study coefficients - reduced-form estimates divided by the pooled first-stage coefficient and multiplied by 100, so that units match the per-$100 PA scaling in the main tables. Each panel regresses the outcome on the leave-one-out peer damage instrument interacted with event-time indicators ($k = -1$ reference period) and includes county and calendar year fixed effects and FEMA PDA and NOAA Storm Events quadratic own-damage controls. Bars show 95% confidence intervals based on standard errors clustered by county.

Appendix E. First-Disaster Sample

As a robustness check, I restrict the sample in three ways: to each county's first observed disaster, to county-disasters with no prior disaster in the preceding five years, and to those with no prior disaster in ten years. The median county experiences four disasters over the sample period (max 16), and the cumulative-treatment design could attenuate per-event effects if later disasters hit counties still recovering from earlier ones.

Table A3 compares IV estimates across all four samples. Coefficients are systematically 2–6× larger in the restricted samples, with a monotonic gradient: full sample < no-disaster-5yr < no-disaster-10yr ≈ first-disaster. The core results - income, unemployment, establishments, house prices, capital outlay, construction - strengthen in every restriction.

The amplified first-disaster effects are also consistent with the Stafford Act obtain-and-maintain requirement (44 CFR § 206.253), under which PA recipients must permanently insure repaired facilities against the type of hazard that caused the original damage. In repeat disasters, insurance proceeds are deducted from PA eligibility, reducing net federal transfers per dollar of damage and attenuating the per-dollar treatment effect. First-time recipients face no such offset.

TABLE A2. Population-Weighted IV Estimates

	UW (ref.)	PW Baseline	PW Non-Adjacent
Income, Employment, and Housing			
Per capita income	0.0253***	0.0468*** (0.0160)	0.0409** (0.0189)
Total income	0.0329***	0.0812*** (0.0195)	0.0783*** (0.0212)
Unemployment rate	-0.3904***	-0.8138*** (0.2638)	-0.8028*** (0.3083)
House price index	13.06***	59.70 (47.06)	39.28 (57.98)
Establishments and Entrepreneurship			
Establishments	0.0239***	0.0248* (0.0131)	0.0165 (0.0172)
Business applications	0.0830***	0.0929*** (0.0316)	0.1150*** (0.0372)
Sole-proprietor revenue	0.0409***	0.0151 (0.0166)	0.0091 (0.0187)
Bus. app. rate	0.6710***	0.6969 (0.4396)	0.5612 (0.4692)
Population and Migration			
Population	0.0067***	0.0336*** (0.0110)	0.0374*** (0.0128)
In-migration flow	0.0782***	0.0477** (0.0195)	0.0486** (0.0226)
Out-migration flow	0.0366***	0.0279 (0.0183)	0.0302 (0.0252)
Local Government Finance			
Capital outlay	0.3679***	0.3203 (0.2052)	0.4145* (0.2279)
Debt outstanding	-0.1495*	-0.2273 (0.3156)	-0.3112 (0.3677)
Eff. ptax rate	-0.0757***	-0.1817*** (0.0572)	-0.1673*** (0.0528)
Muni yield (%)	-0.2964*	-0.3175 (0.3714)	-0.4525 (0.3528)
Banking and Credit			
Bank deposits	0.0302**	0.0228 (0.0452)	0.0617 (0.0403)
Bank net income	0.0655***	-0.0215 (0.0617)	0.0362 (0.0627)
NPL ratio	-0.0024***	-0.0091*** (0.0019)	-0.0079*** (0.0019)
Construction			
Gov. construction	0.4159***	0.2310 (0.2918)	0.2297 (0.2723)
Constr. RE loans	0.1119***	0.0186 (0.0519)	0.0346 (0.0583)
Constr. establishments	0.0490***	0.0344* (0.0184)	0.0307 (0.0252)
Constr. earnings	0.0888***	0.2240*** (0.0450)	0.2335*** (0.0501)
N county-disasters	9,053	9,053	8,847
KP *F*	9–51	24–47	16–43

Notes: Each row reports the IV estimate of the effect of $100 per capita cumulative PA on each outcome. "UW (ref.)" reproduces the unweighted Panel B coefficient from the main tables. "PW Baseline" weights observations by county population. "PW Non-Adjacent" weights by population and additionally excludes geographically contiguous peer counties from the instrument. All specifications include county and year fixed effects and FEMA + Storm quadratic own-damage controls. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

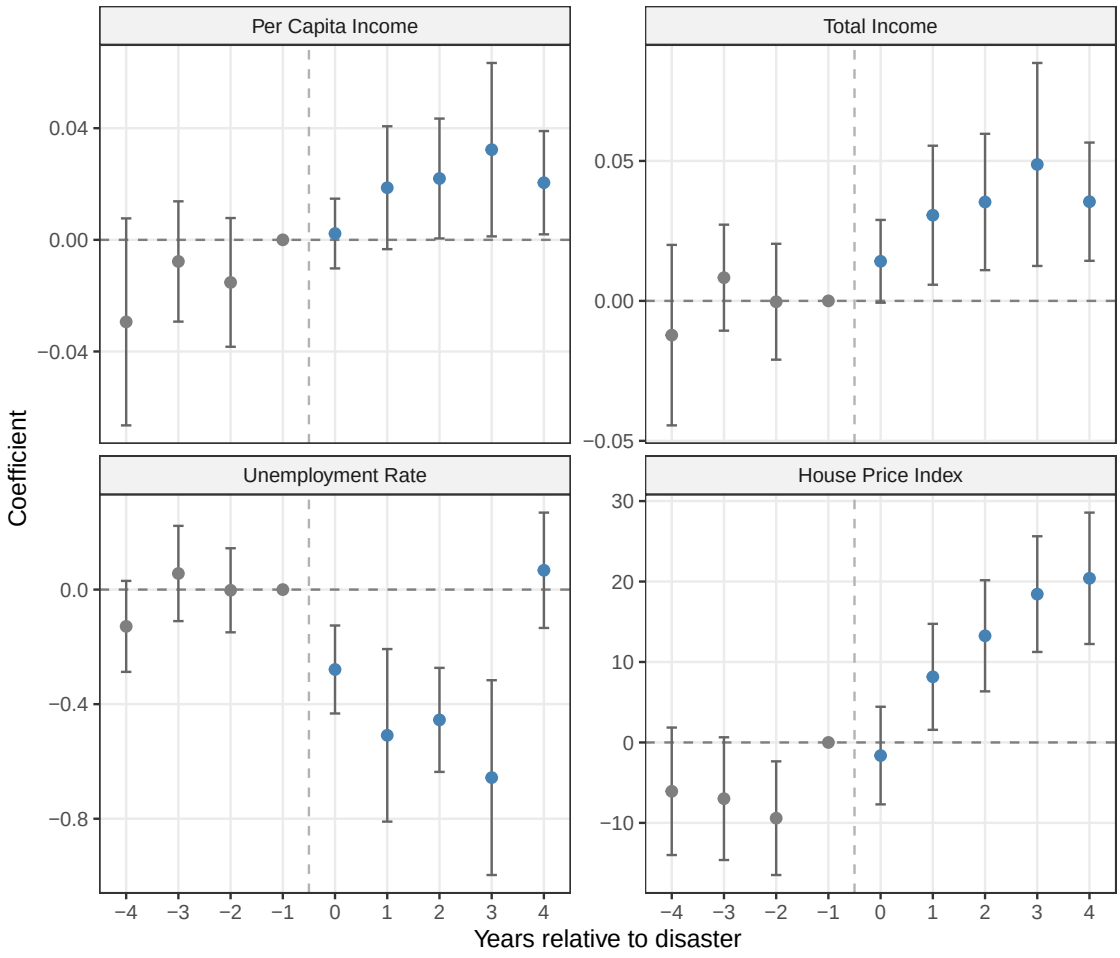


FIGURE A2. Reduced-Form Event Studies: Income, Employment, and Housing

Notes: Outcomes corresponding to Table 3. Per capita income and total income from BEA CAINC1; unemployment rate from BLS LAUS; house price index from FHFA.

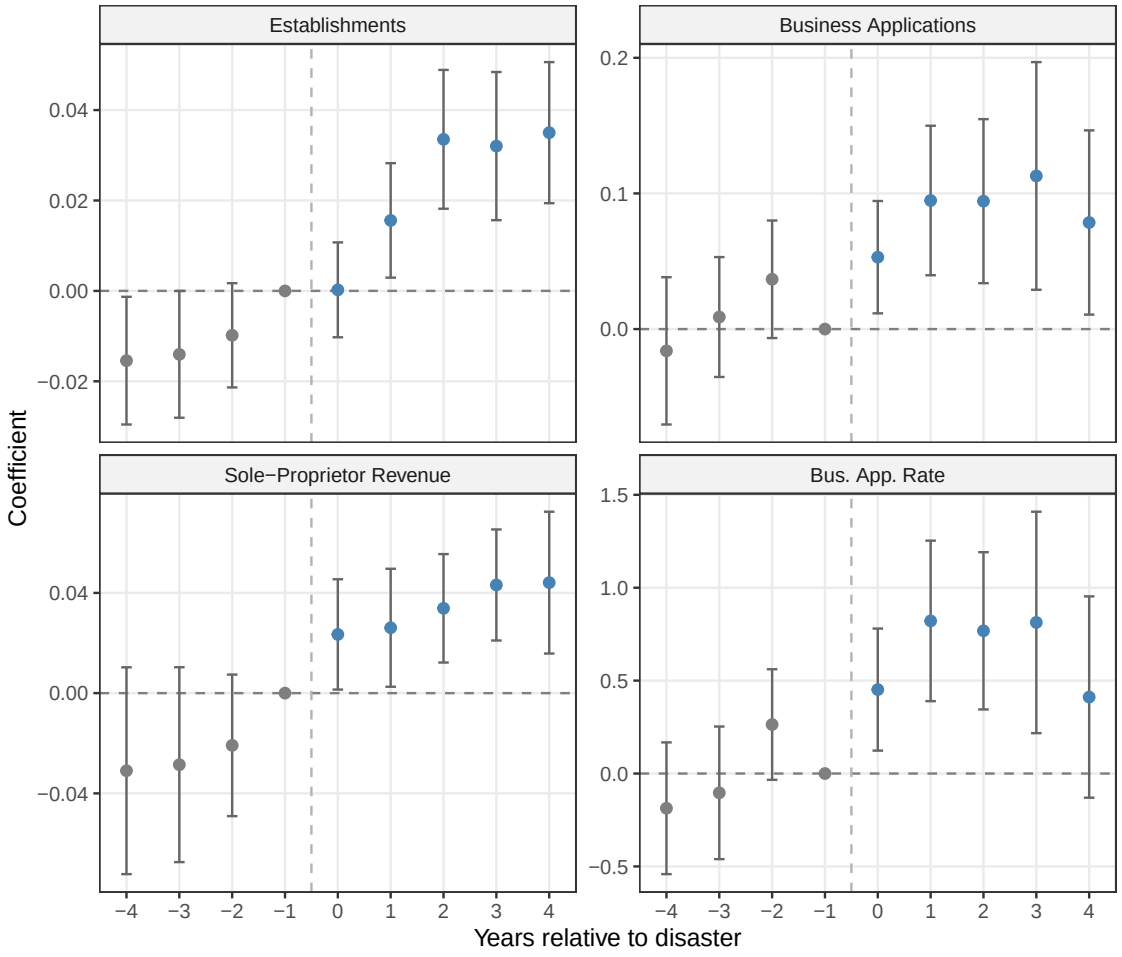


FIGURE A3. Reduced-Form Event Studies: Establishments and Entrepreneurship

Notes: Outcomes corresponding to Table 4. Establishments from Census CBP (all-industry total); business applications from Census Business Formation Statistics (2005–2024); nonemployer receipts from Census Nonemployer Statistics (1997–2022); business application rate is applications per 1,000 population.

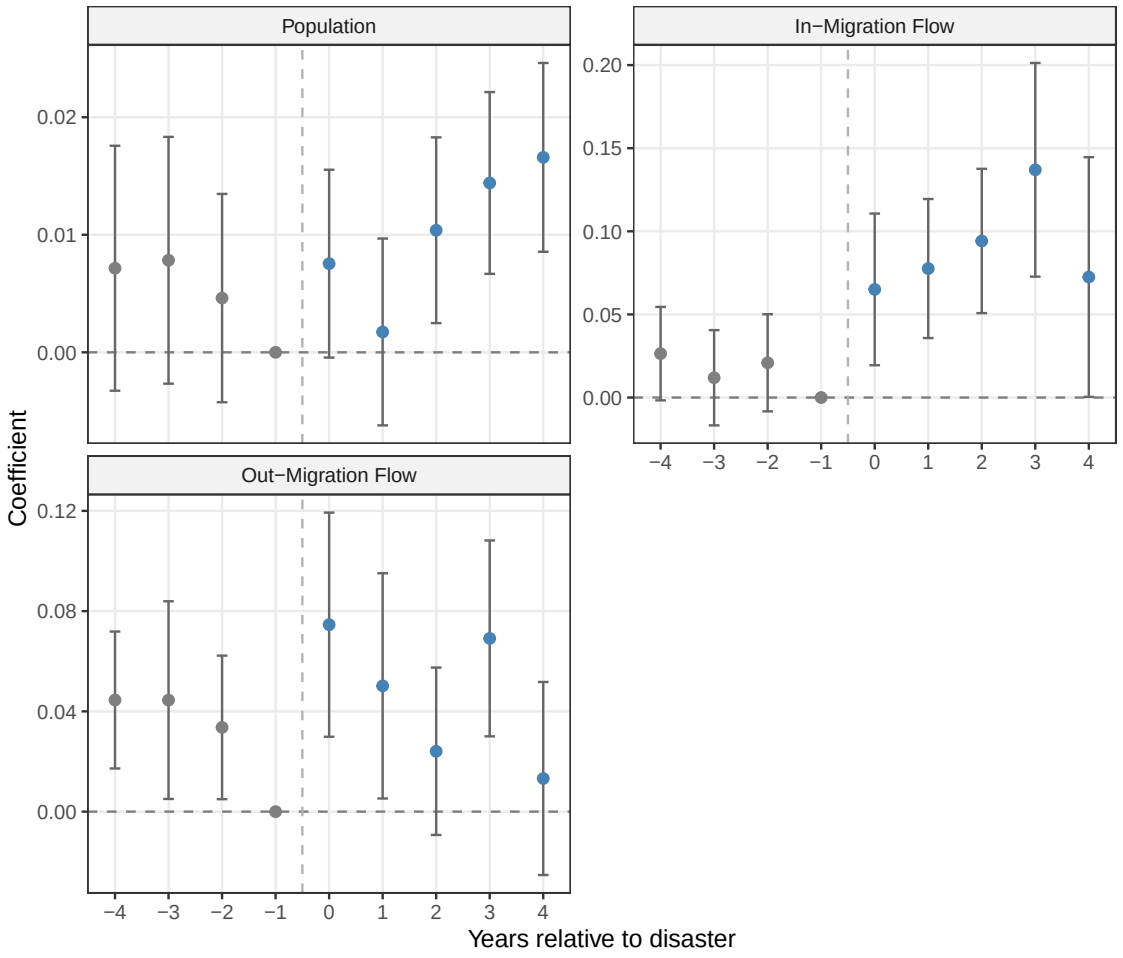


FIGURE A4. Reduced-Form Event Studies: Population and Migration

Notes: Outcomes corresponding to Table 5. Population derived from Census SAIPE (1997–2023); in-migration and out-migration from IRS Statistics of Income county-level tax return flows.

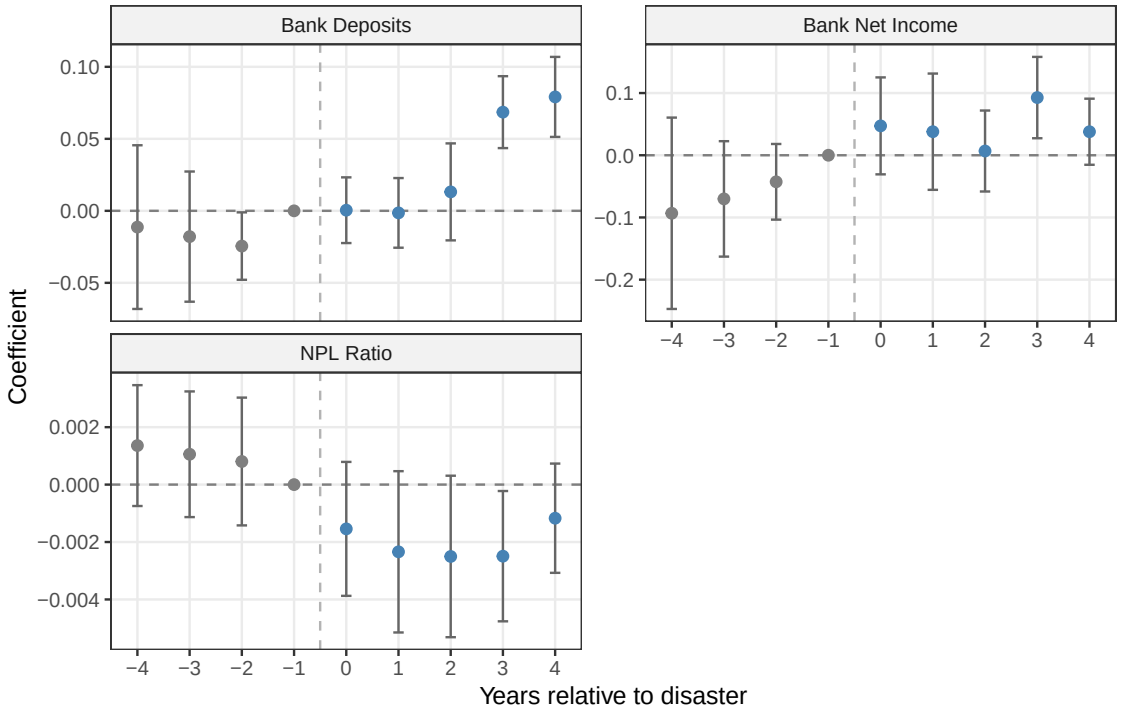


FIGURE A5. Reduced-Form Event Studies: Banking and Credit

Notes: Outcomes corresponding to Table A15. Bank deposits from FDIC Summary of Deposits (1994–2023); net income and NPL ratio from FDIC Call Reports allocated to counties using branch deposit share weights (1994–2023). NPL ratio is noncurrent loans divided by total loans.

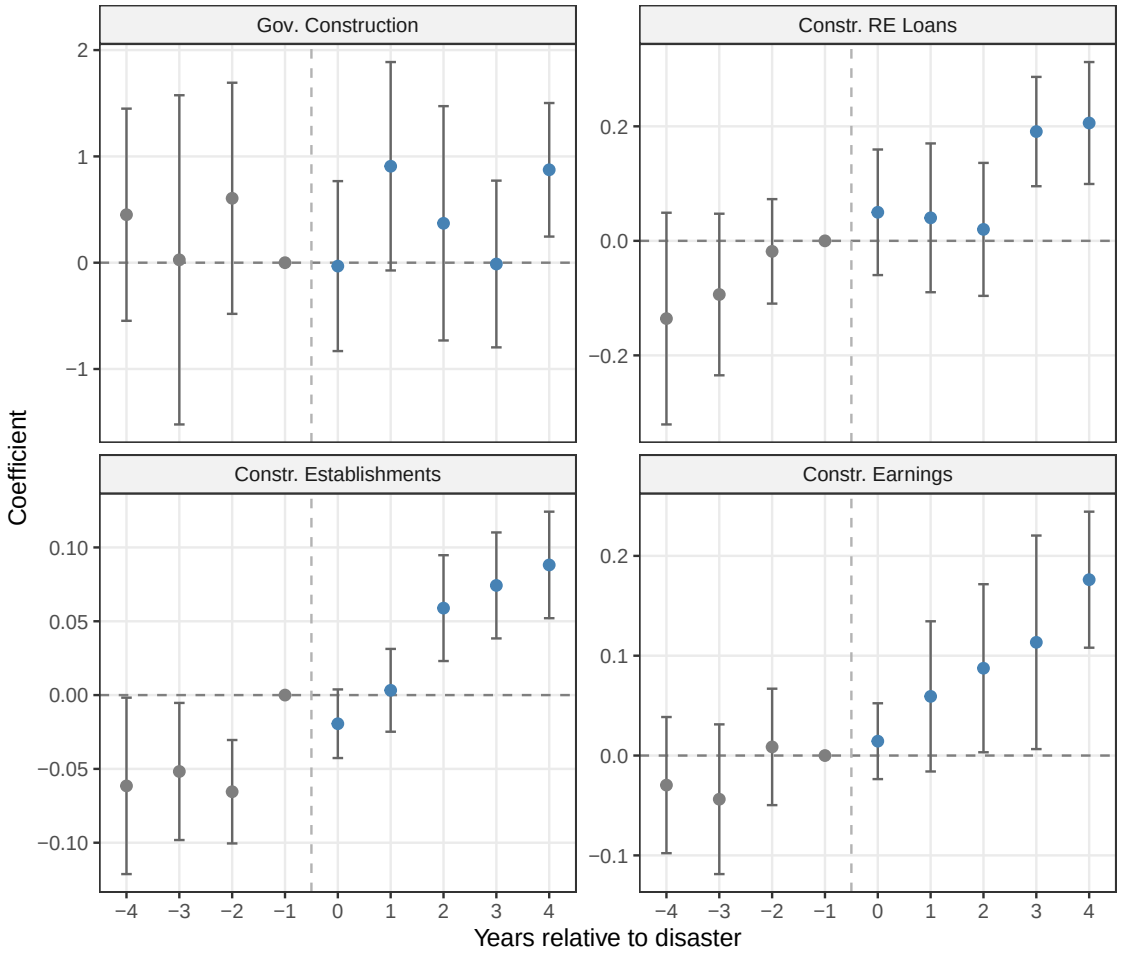


FIGURE A6. Reduced-Form Event Studies: Construction Sector

Notes: Outcomes corresponding to Table 6. Government construction expenditure from the Government Finance Database (Census of Governments, 1992–2022; sparse event-time grid because of 5-year census spacing). Construction and land-development loans from FDIC Call Reports. Construction establishments from Census County Business Patterns NAICS 23. Construction earnings from BEA CAINC5N (NAICS 23, 2001–2024).

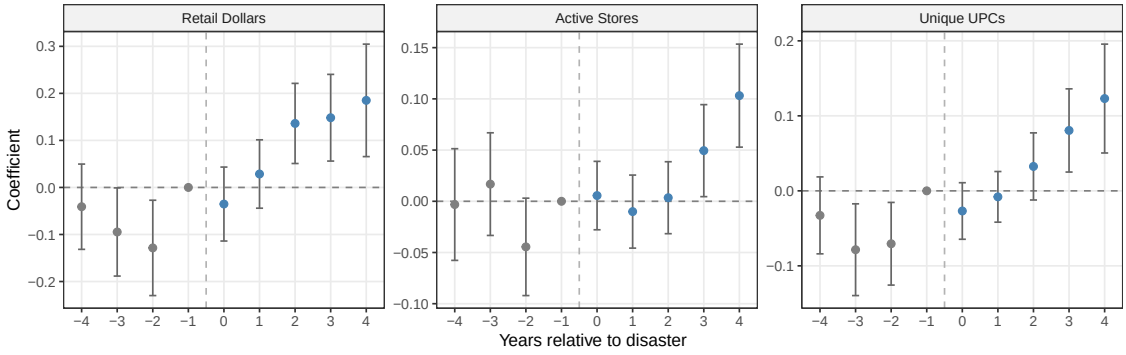


FIGURE A7. Reduced-Form Event Studies: Retail Activity

Notes: Outcomes corresponding to Table 7. Nielsen Retail Scanner (2006–2017; see Appendix A.22 on why the panel stops in 2017), aggregated to the county-year from store-week-UPC transaction records at participating grocery, drug, mass-merchandiser, and convenience retailers.

TABLE A3. Restricted Samples: First Disaster and No Recent Disaster

	Baseline	First disaster	No disaster 5yr	No disaster 10yr
Income, Employment, and Housing				
Per capita income	0.0253*** (0.0073)	0.0917*** (0.0318)	0.0431*** (0.0146)	0.0773*** (0.0241)
Total income	0.0329*** (0.0087)	0.0822*** (0.0306)	0.0430*** (0.0149)	0.0722*** (0.0233)
Unemployment rate	-0.3904*** (0.0929)	-1.146*** (0.2222)	-0.8030*** (0.2140)	-1.050*** (0.1828)
House price index	13.06*** (3.659)	41.04*** (11.62)	16.91** (6.721)	36.13*** (9.908)
Establishments and Entrepreneurship				
Establishments	0.0239*** (0.0062)	0.0382*** (0.0118)	0.0186*** (0.0069)	0.0325*** (0.0096)
Business applications	0.0830*** (0.0189)	0.1179*** (0.0453)	0.0926*** (0.0294)	0.1071*** (0.0361)
Sole-proprietor revenue	0.0409*** (0.0095)	0.1259*** (0.0293)	0.0474*** (0.0144)	0.0999*** (0.0222)
Bus. app. rate	0.6710*** (0.1524)	0.7873*** (0.2576)	0.6688*** (0.2212)	0.7532*** (0.2346)
Population and Migration				
Population	0.0067*** (0.0026)	0.0000 (0.0056)	0.0009 (0.0034)	0.0016 (0.0053)
In-migration flow	0.0782*** (0.0193)	0.1332*** (0.0311)	0.1160*** (0.0359)	0.1474*** (0.0288)
Out-migration flow	0.0366*** (0.0123)	-0.0337* (0.0198)	0.0336** (0.0160)	-0.0014 (0.0175)
Local Government Finance				
Capital outlay	0.3679*** (0.1160)	0.5651** (0.2315)	0.4240** (0.1669)	0.4388** (0.1967)
Debt outstanding	-0.1495* (0.0791)	-0.1400 (0.1088)	-0.1452 (0.0943)	-0.1243 (0.1091)
Eff. ptax rate	-0.0757*** (0.0289)	-0.0876** (0.0417)	-0.0813** (0.0347)	-0.0895** (0.0409)
Muni yield (%)	-0.2964* (0.1516)	-1.010 (0.7450)	-0.5256 (0.3334)	-1.059* (0.5819)
Banking and Credit				
Bank deposits	0.0302** (0.0118)	0.0616 (0.0508)	0.0178 (0.0179)	0.0493 (0.0379)
Bank net income	0.0655*** (0.0243)	0.1405 (0.1005)	0.0770* (0.0409)	0.1419* (0.0794)
NPL ratio	-0.0024*** (0.0008)	-0.0055*** (0.0018)	-0.0031** (0.0013)	-0.0059*** (0.0016)
Construction				
Gov. construction	0.4159*** (0.1502)	0.6628** (0.2931)	0.5079** (0.1996)	0.4507* (0.2574)
Constr. RE loans	0.1119*** (0.0390)	0.1782 (0.1253)	0.0917 (0.0570)	0.1857* (0.1039)
Constr. establishments	0.0490*** (0.0128)	0.1613*** (0.0441)	0.0527*** (0.0179)	0.1414*** (0.0347)
Constr. earnings	0.0888*** (0.0254)	0.1459* (0.0760)	0.0981** (0.0396)	0.1637** (0.0658)
N county-disasters	9,053	2,544	3,950	2,694
KP *F*	9–51	4–18	4–24	4–23

Notes: Each cell reports the IV estimate of the effect of $100 per capita cumulative PA on each outcome. "Baseline" reproduces the unweighted IV estimates from the main tables. "First disaster" restricts to each county's first observed disaster in the sample. "No disaster 5yr" ("No disaster 10yr") restricts to county-disasters where the county had no other disaster declaration in the preceding 5 (10) years. All specifications include county and year fixed effects and FEMA + Storm quadratic own-damage controls. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix F. Construction-Channel Share Calculations

This appendix reports the back-of-envelope calculations behind the statement in Section 4.4 that construction accounts for roughly 10% of the income effect and 23% of the establishment effect.

Earnings.. Decomposing the total-income effect into sectoral contributions requires the share of construction earnings in total personal income. From BEA CAINC5N over the disaster sample, the construction share of total earnings averages 3.56% damage-weighted (3.75% unweighted; median 3.41%). Construction earnings rise by 8.9% per \$100/pc PA. The implied contribution is $0.0356 \times 8.9 = 0.32$ percentage points out of a 3.26 percentage point total-income effect, or 9.7%.

Establishments.. For the establishment decomposition, Census CBP gives the share of construction (NAICS 23) in total establishments at 10.88% damage-weighted (10.73% unweighted; median 10.26%). Construction establishments rise by 4.89% per \$100/pc PA. The implied contribution is $0.1088 \times 4.89 = 0.53$ percentage points out of a 2.36 percentage point total-establishment effect, or 22.6%.

Interpretation.. The asymmetry (one-tenth of income, one-fifth of establishments) reflects that construction firms enter at high rates following disasters - specialty-trade contractors and out-of-area builders setting up local offices to bid on PA-funded work - but these new entrants are small. They add many establishments per dollar of payroll. The remaining 77–90% of both effects flows through demand spillovers into retail, services, finance, and government employment in the affected counties.

The computations use the same disaster sample as the IV regressions and the latest available BEA and CBP releases at the time of writing.

Appendix G. Federal Spending Controls

A potential threat to identification is that the instrument captures variation in overall disaster severity, which triggers multiple federal programs beyond PA. If these other programs also affect outcomes, the IV estimate conflates PA with the

broader federal response. I address this by testing whether the instrument predicts other federal disaster spending programs and by showing that controlling for them leaves PA coefficients unchanged.

Table A4 reports first-stage regressions with each federal program as the dependent variable, using the same specification as the main PA first stage. The instrument strongly predicts PA (column 1, KP $F = 11.7$) but does not predict NFIP insurance claims ($p = 0.261$), SBA disaster loans ($p = 0.254$), or FEMA Individual Assistance ($p = 0.325$). CDBG-DR is marginal ($p = 0.062$) under equal weighting but null under population weighting ($p = 0.418$). Column (6) tests combined highway spending per capita - state highway expenditure from the Government Finance Database plus FHWA Emergency Relief - and finds it is not predicted by the instrument ($p = 0.268$), as the positive state component and negative federal component offset. PA is uniquely responsive to the instrument because it is the only program where FEMA's operational presence - damage assessors, field offices, technical assistance - directly drives the application process on behalf of county governments. NFIP claims, SBA loans, and IA are demand-driven: amounts depend on individual applications and eligibility, not on the scale of FEMA's field operations.

Table A5 compares IV coefficients under three specifications: the baseline, a specification that additionally controls for Individual Assistance, NFIP claims, SBA loans, and CDBG-DR per capita,[24] and a specification that further adds combined highway spending per capita. Across all outcomes, the county-level federal controls change coefficients by at most 3%. Adding combined highway spending changes coefficients by at most 11%, with all outcomes retaining their sign and significance.

I also test state-level private insured losses from NAIC statutory filings in commercial multiple peril, fire, inland marine, and allied lines. I measure excess losses as the disaster-year level minus the average of adjacent years and apportion state totals to counties by their share of assessed damage, excluding state-years with expedited major disaster declarations whose losses are not attributable to the analysis sample. The instrument does not predict these excess losses ($p = 0.219$), and controlling for them changes PA coefficients by less than 1%.

Table A6 reports summary statistics for the 2020–2025 subsample where FHWA

[24] CDBG-DR allocations are observed at the state level from HUD financial reports and allocated to counties proportional to assessed damage within each state-disaster pair.

Emergency Relief allocations are observed. FHWA-ER is a substantial federal spending channel: the damage-weighted mean is $149 per capita, comparable to PA federal ($163) and CDBG-DR ($138) at the damage-weighted level. 38% of county-disasters in this period receive nonzero FHWA-ER. Despite its magnitude, the instrument does not predict combined highway spending ($p = 0.268$, Table A4 column 6), and controlling for it changes PA coefficients by at most 11% (Table A5).

TABLE A4. Instrument Diagnostics: Does Peer Damage Predict Non-PA Spending?

Dependent variable	LOO peer damage/cap coef. (SE)	N (panel obs.)	KP F
Cumulative PA/capita	0.1110*** (0.0325)	82,467	11.6
NFIP claims/capita	-0.0044 (0.0036)	82,467	1.5
SBA disaster loans/capita	-0.0016 (0.0012)	82,467	1.6
CDBG-DR/capita	-0.0337* (0.0178)	82,467	3.6
Individual Assistance/capita	-0.0012 (0.0012)	82,467	1.0
Total highway/cap	0.0308 (0.0279)	82,467	1.2

Notes: Each row regresses a per-capita spending outcome (interacted with a post-declaration indicator) on the leave-one-out peer damage instrument. The first row is the first stage for PA. The remaining rows test whether the instrument predicts NFIP claims, SBA disaster loans, CDBG-DR, and Individual Assistance, all per capita; the final row tests combined highway spending per capita (state highway expenditure from the Government Finance Database plus FHWA Emergency Relief for FY2020–2025). All specifications include county and year fixed effects and FEMA + Storm quadratic own-damage controls. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix H. Total Transfers as Exclusion Restriction Support

If the leave-one-out peer damage instrument operated through channels other than PA allocation - for example, by attracting generalized federal attention to the focal county - one would expect all categories of federal transfer payments to rise with the instrument. I test this by regressing log transfer payments (BEA CAINC35) on instrumented PA. Table A7 reports the results. Total transfer payments are insignificant ($p = 0.70$), with a point estimate implying roughly $8 per capita per $100 of PA - economically small relative to the mean transfer level of approximately $7,000 per capita, and with a 95% confidence interval spanning negative values. Retirement and disability transfers, which account for approximately 60% of total transfers and are determined by federal benefit formulas unrelated to disaster aid, show a precisely estimated zero ($p = 0.81$). The subcategories that do move - medical transfers increase by 0.9% ($p = 0.067$), consistent with FEMA

TABLE A5. Robustness to Controlling for All Observable Federal and State Disaster Spending

	Baseline	+ All Federal	+ All Fed & State Hwy
Log per capita income	0.025*** (0.007)	0.025*** (0.007)	0.023*** (0.007)
Log total income	0.033*** (0.009)	0.032*** (0.008)	0.030*** (0.008)
Unemployment rate	-0.390*** (0.093)	-0.386*** (0.091)	-0.392*** (0.093)
House price index	13.055*** (3.659)	12.822*** (3.574)	12.218*** (3.477)
Log establishments	0.024*** (0.006)	0.024*** (0.006)	0.021*** (0.006)
Log business apps	0.083*** (0.019)	0.082*** (0.018)	0.078*** (0.018)
Log nonemp. receipts	0.041*** (0.010)	0.040*** (0.009)	0.037*** (0.009)
Bus. app. rate	0.671*** (0.152)	0.664*** (0.150)	0.637*** (0.147)
Log population	0.007*** (0.003)	0.007*** (0.003)	0.006** (0.002)
Log in-migration	0.078*** (0.019)	0.077*** (0.019)	0.073*** (0.019)
Log out-migration	0.037*** (0.012)	0.036*** (0.012)	0.035*** (0.012)
Log capital outlay	0.368*** (0.116)	0.365*** (0.115)	0.347*** (0.115)
Log debt outstanding	-0.150* (0.079)	-0.149* (0.079)	-0.164** (0.080)
Log eff. ptax rate	-0.076*** (0.029)	-0.075*** (0.029)	-0.076*** (0.029)
Muni offering yield	-0.296* (0.152)	-0.305** (0.155)	-0.303* (0.160)
Log bank deposits	0.030** (0.012)	0.030** (0.012)	0.026** (0.012)
Log bank net income	0.066*** (0.024)	0.065*** (0.024)	0.059** (0.024)
NPL ratio	-0.002*** (0.001)	-0.002*** (0.001)	-0.003*** (0.001)
Log gov. construction	0.416*** (0.150)	0.411*** (0.149)	0.373** (0.150)
Log constr. RE loans	0.112*** (0.039)	0.111*** (0.038)	0.096** (0.038)
Log constr. establishments	0.049*** (0.013)	0.048*** (0.013)	0.043*** (0.012)
Log constr. earnings	0.089*** (0.025)	0.087*** (0.025)	0.080*** (0.023)
N (panel obs.)	77,667	77,667	77,667
KP F	9–51	9–52	9–51

Notes: Each cell reports the IV estimate of the effect of $100 per capita cumulative PA on each outcome. "Baseline" matches the main tables (county + year fixed effects and FEMA + Storm quadratic own-damage controls). "+ All Federal" additionally controls for Individual Assistance, NFIP claims, SBA disaster loans, and CDBG-DR, all per capita. "+ All Fed & State Hwy" further controls for combined highway spending per capita (state highway expenditure from the Government Finance Database plus FHWA Emergency Relief for FY2020–2025). Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A6. Summary Statistics: 2020–2025 Subsample with FHWA Emergency Relief

	Median	Mean	Dmg-Wt. Mean	P25	P75
Panel A: Disaster Characteristics					
County population	19,590	83,113	34,780	8,964	44,558
Counties per disaster	17	21	18	10	25
Assessed damage/capita	$14	$42	$274	$7	$35
PA federal/capita	$6.9	$43.8	$163.6	$0.5	$29.1
PA state-local/capita	$2.3	$14.6	$54.5	$0.2	$9.7
PA projects per county	7	15	17	3	17
IA/capita	$0.0	$4.4	$9.8	$0.0	$0.0
NFIP claims/capita	$0.0	$2.2	$4.7	$0.0	$0.0
SBA disaster loans/capita	$0.0	$1.9	$4.4	$0.0	$0.0
CDBG-DR/capita	$0.0	$49.4	$138.0	$0.0	$0.0
FHWA Emergency Relief/capita	$0.0	$13.9	$148.8	$0.0	$2.0
Panel B: Pre-Disaster Conditions $(t-1)$					
Unemployment rate (%)	3.9	4.4	4.4	2.8	5.4
Per capita income	$45,866	$49,080	$49,985	$39,152	$56,570
House price index	268.1	365.6	310.0	199.0	398.4
Establishments	369	2,000	872	181	1,018
Panel C: Post-Disaster Conditions $(t+2)$					
Unemployment rate (%)	3.4	3.7	4.0	2.8	4.3
Per capita income	$45,753	$49,022	$49,571	$39,441	$55,657
House price index	327.4	440.6	405.9	250.1	476.6
Establishments	500	2,149	1,077	220	1,272

Notes: Summary statistics for the 2020–2025 subsample for which FHWA Emergency Relief data are available. The data include 2,167 county-disasters from 2020–2025 for which a non-expedited PDA was requested for more than 2 counties in a state. Dollar amounts in 2020 dollars. Panel A reports county characteristics and details of post-disaster spending, including FHWA-ER allocations. Panels B and C show pre-disaster $(t-1)$ and post-disaster $(t+2)$ county-level economic and financial conditions. All other variables defined as in Table 1.

Disaster Recovery Centers facilitating Medicaid enrollment, and veterans' benefits decrease by 5.9% ($p < 0.001$), consistent with the Stafford Act duplication-of-benefits offset - net to approximately zero in the aggregate.

TABLE A7. Government Transfer Payments: IV Estimates

Transfer category	PA per cap (×100) coef. (SE)	N (panel obs.)	KP F
Total	0.0012 (0.0031)	72,016	15
Retirement	-0.0009 (0.0037)	72,016	15
Medical	0.0086* (0.0047)	72,016	15
Income Maint.	0.0103** (0.0046)	72,016	15
Unemployment Ins.	0.0490*** (0.0183)	72,016	15
Veterans	-0.0588*** (0.0143)	72,016	15

Notes: Each row reports the IV estimate of the effect of $100 per capita cumulative FEMA Public Assistance on the log of government transfer payments by category (BEA CAINC35). Transfer categories: total personal current transfer receipts, retirement and disability insurance benefits (OASDI), medical benefits (Medicare/Medicaid), income maintenance, unemployment insurance compensation, and veterans' benefits. All specifications include county and year fixed effects and FEMA + Storm quadratic own-damage controls. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix I. Spillover Tests

A direct test of whether PA spending spills across county borders is to instrument focal county i's PA with i's leave-one-out peer damage and ask whether it affects adjacent county j's outcomes. I restrict neighbor j to counties that are (i) not included in the same disaster declaration and (ii) have no NOAA Storm Events recorded within ±90 days of the declaration date. This second restriction is important: 84% of adjacent non-declared counties experienced storm activity near the disaster date, and including them produces spurious spillovers driven by direct storm exposure rather than PA transmission. With truly clean neighbors - 4,519 focal-neighbor pairs across 1,501 unique neighbor counties - I regress j's outcomes on i's instrumented PA, with neighbor county and calendar year fixed effects, clustering two-way on focal and neighbor county. Table A8 reports the results. Ten of eleven outcomes show null spillovers. The exception is unemployment, consistent with shared commuting zones transmitting employment gains to adjacent labor markets. PA's effects are otherwise localized to the recipient county.

As a complementary test, I split the sample by the number of adjacent counties

TABLE A8. Spatial Spillover Tests: Own-County Effects vs. Truly Clean Neighbor Spillovers

	Own County Effect	Neighbor Spillover
Panel A: Income, Employment, and Housing		
Per capita income (log)	0.0253*** (0.0073)	0.0150 (0.0326)
Total income (log)	0.0329*** (0.0087)	0.0063 (0.0438)
Unemployment rate	-0.3904*** (0.0929)	-1.6** (0.6836)
House price index	13.1*** (3.7)	-2.8 (37.6)
Panel B: Establishments and Entrepreneurship		
Establishments (log)	0.0239*** (0.0062)	0.0550** (0.0257)
Business applications (log)	0.0830*** (0.0189)	0.0202 (0.1416)
Nonemployer receipts (log)	0.0409*** (0.0095)	0.0554 (0.0383)
Bus. app. rate	0.6710*** (0.1524)	1.1 (1.3)
Panel C: Population and Migration		
Population (log)	0.0067*** (0.0026)	-0.0087 (0.0158)
In-migration returns (log)	0.0782*** (0.0193)	-0.0181 (0.1381)
Out-migration returns (log)	0.0366*** (0.0123)	-0.0011 (0.0570)
Panel D: Local Government Finance		
Capital outlay (log)	0.3679*** (0.1160)	0.3522 (0.2326)
Debt outstanding (log)	-0.1495* (0.0791)	-0.1672 (0.2686)
Eff. ptax rate (log)	-0.0757*** (0.0289)	-0.1568* (0.0911)
Muni offering yield	-0.2964* (0.1516)	0.0873 (0.1977)
Panel E: Banking and Credit		
Bank deposits (log)	0.0302** (0.0118)	0.0577** (0.0239)
Bank net income (log)	0.0655*** (0.0243)	0.0664 (0.0444)
NPL ratio	-0.0024*** (8e-04)	-0.0040* (0.0023)
Panel F: Construction		
Gov. construction (log)	0.4159*** (0.1502)	0.4030 (0.3233)
Constr. RE loans (log)	0.1119*** (0.0390)	-0.0205 (0.0709)
Constr. establishments (log)	0.0490*** (0.0128)	0.1023** (0.0492)
Constr. earnings (log)	0.0888*** (0.0254)	0.0328 (0.1390)
N focal-neighbor pairs		4,700–34,891
KP *F* (spillover)		3.9–8.7

Notes: Each row reports the effect of $100 per capita cumulative PA on each outcome. "Own County Effect" reproduces the IV estimate from the main tables. "Neighbor Spillover" instruments focal-county PA with focal-county leave-one-out peer damage; the dependent variable is measured in adjacent counties not included in the same disaster declaration and with no NOAA Storm Events within ±90 days of the declaration date. The neighbor sample includes 4,519 focal-neighbor pairs across 1,501 unique neighbor counties. All specifications include county and year fixed effects and FEMA + Storm quadratic own-damage controls. Standard errors clustered by county for own effects, two-way by focal and neighbor county for spillovers. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

included in the same disaster declaration: n = 1–3, n = 4–6, and n = 7–9. If PA spillovers from co-declared neighbors inflated the IV estimates, coefficients should grow with n. I find the opposite: coefficients are systematically largest in the n = 1–3 bin and decline monotonically (Table A9). Per capita income is +5.1% with 1–3 co-declared neighbors versus +2.0% with 4–6; unemployment is −0.69pp versus −0.23pp; business applications are +17.5% versus +4.4%. This declining gradient primarily reflects crowd-out dilution - in larger disasters, FEMA's budget is spread across more claimants, attenuating the per-county effect - but is also inconsistent with positive PA spillovers inflating the estimates.

Appendix J. Adjacent-Neighbor Damage Controls

The non-adjacent instrument addresses the concern that trade linkages with nearby damaged peers violate the exclusion restriction by removing adjacent counties from the instrument. A complementary approach retains the non-adjacent instrument and additionally controls for the average damage per capita of adjacent disaster-affected counties, interacted with a post-declaration indicator. This directly absorbs any effect of nearby destruction on the focal county's outcomes - whether through business reallocation, supply chain disruption, or demand spillovers - while the instrument identifies PA variation from geographically distant peers.

Table A10 reports three specifications for all 22 outcomes: the baseline IV, the non-adjacent IV alone, and the non-adjacent IV with the adjacent damage control. Of 18 outcomes that are significant in the baseline, 17 remain significant with the adjacent damage control. Coefficients move away from zero for 15 of 22 outcomes, with a median increase of 10%. Per capita income is essentially unchanged (+2.48% versus +2.52%); unemployment strengthens from −0.39pp to −0.43pp; house prices increase from +12.9 to +18.3 index points; business applications rise from +8.3% to +10.9%. The one outcome that loses significance is the municipal offering yield, which was already borderline (p = 0.049) in a small rated subsample. Kleibergen-Paap F-statistics decline modestly (median 12 to 11) but remain adequate across all outcomes.

I further split the sample by the share of total disaster damage originating from adjacent counties - a direct measure of how much of the instrument's variation comes from nearby peers. Table A11 reports IV estimates by quartile of adjacent

TABLE A9. IV Estimates by Number of Treated Neighbors in Same Disaster

	Full	n = 1–3	n = 4–6	n = 7–9
Income, Employment, and Housing				
Per capita income (log)	0.0253*** (0.0073)	0.0513*** (0.0156)	0.0200*** (0.0069)	0.0321 (0.0208)
Total income (log)	0.0329*** (0.0087)	0.0650*** (0.0184)	0.0217*** (0.0076)	0.0364 (0.0252)
Unemployment rate	−0.390*** (0.093)	−0.690*** (0.211)	−0.233*** (0.077)	−0.027 (0.139)
House price index	13.06*** (3.66)	18.78** (9.26)	8.06*** (2.58)	11.81 (7.63)
Establishments and Entrepreneurship				
Establishments (log)	0.0239*** (0.0062)	0.0304** (0.0121)	0.0183** (0.0074)	0.0161 (0.0112)
Business applications (log)	0.0830*** (0.0189)	0.1745*** (0.0410)	0.0443*** (0.0162)	0.0267 (0.0516)
Nonemployer receipts (log)	0.0409*** (0.0095)	0.0763*** (0.0203)	0.0205*** (0.0076)	0.0429* (0.0256)
Bus. app. rate (per 1K)	0.671*** (0.152)	1.350*** (0.343)	0.287** (0.115)	0.310 (0.455)
Population and Migration				
Population (log)	0.0067*** (0.0026)	0.0108 (0.0066)	0.0034* (0.0020)	0.0054 (0.0073)
In-migration (log)	0.0782*** (0.0193)	0.1488*** (0.0453)	0.0431*** (0.0152)	0.0410 (0.0366)
Out-migration (log)	0.0366*** (0.0123)	0.0749*** (0.0285)	0.0216** (0.0106)	0.0236 (0.0263)
Local Government Finance				
Capital outlay (log)	0.3679*** (0.1160)	0.2687 (0.1843)	0.2094** (0.0852)	—
Debt outstanding (log)	−0.1495* (0.0791)	−0.2334 (0.1722)	0.0402 (0.0980)	—
Eff. ptax rate (log)	−0.0757*** (0.0289)	−0.0716 (0.0669)	−0.0564** (0.0234)	—
Muni offering yield	−0.296* (0.152)	−0.015 (0.322)	−0.410 (0.255)	—
Banking and Credit				
Bank deposits (log)	0.0302** (0.0118)	0.0552*** (0.0191)	0.0265*** (0.0094)	0.0205 (0.0176)
Bank net income (log)	0.0655*** (0.0243)	0.1632*** (0.0621)	0.0451** (0.0181)	0.0227 (0.0369)
NPL ratio	−0.0024*** (0.0008)	−0.0062*** (0.0020)	−0.0006 (0.0006)	−0.0009 (0.0014)
Construction				
Gov. construction (log)	0.4159*** (0.1502)	0.0732 (0.2527)	0.3205** (0.1346)	—
Constr. RE loans (log)	0.1119*** (0.0390)	0.2011*** (0.0743)	0.1166*** (0.0363)	0.0838 (0.0684)
Constr. establishments (log)	0.0490*** (0.0128)	0.0846*** (0.0285)	0.0356*** (0.0127)	0.0600 (0.0396)
Constr. earnings (log)	0.0888*** (0.0254)	0.2360*** (0.0619)	0.0465*** (0.0180)	0.0875* (0.0499)
N county-disasters	9,067	5,276	3,037	190
KP F	9–51	21–60	6–24	4–8

Notes: Each cell reports the IV coefficient from the preferred specification (unweighted-mean LOO peer damage instrument, FEMA + Storm quadratic own-damage controls). n denotes the number of other counties in the same disaster declaration that are geographically adjacent to the focal county. The full sample includes all county-disasters regardless of neighbor count. Public finance outcomes (capital outlay, construction, debt, effective property tax rate) use Census of Governments data available in census years only and are omitted for n = 7–9 due to insufficient observations. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

damage share. For 8 of 10 outcomes, coefficients are largest in Q1 (lowest adjacent share) and decline toward Q4 (highest). Per capita income is +4.1% in Q1 versus +0.9% in Q4; capital outlay is +79% versus +17%; debt outstanding is −43% versus −5%. This gradient is consistent with adjacent damage acting as a weak negative confounder: when more instrument variation comes from nearby peers, the downward bias is largest.

If the IV estimates reflected business stealing from damaged neighbors rather than a genuine fiscal multiplier, controlling for adjacent-county damage should shrink the coefficients toward zero - the putative confound would be absorbed. The opposite pattern rules out this interpretation.

Appendix K. Robustness to Damage Mismeasurement

The identification strategy conditions on own assessed damage and instruments aid with peer assessed damage, both taken from the same FEMA Preliminary Damage Assessments. These are rapid field estimates measured with considerable error. Purely idiosyncratic error attenuates the estimates, but a component of the error common to every county in a disaster - a generous or stringent assessment applied event-wide - is shared between the instrument and the own-damage control and is not absorbed by the county and year fixed effects, since disasters fall within years. Common error of this kind could bias the estimates in either direction. I assess it directly by replacing the FEMA assessment with physically modeled hazard intensity built independently of FEMA: the GloFAS river-discharge flood return period of Farkas and Kim (2025) and modeled maximum sustained hurricane wind from the parametric vortex model of Willoughby et al. (2006) applied to NOAA HURDAT2 best-track data. Both measures exist for flood- and hurricane-classified disasters, to which I restrict throughout this exercise. The physical instrument uses the identical within-disaster leave-one-out construction as the baseline; only the underlying hazard measure changes.

Table A12 reports the crossing. Column (1) reproduces the main-paper estimate on the full sample. Columns (2)–(6) restrict to the physically measured subsample, holding the sample fixed so the remaining columns are comparable: column (2) repeats the baseline, column (3) replaces the own-damage control with physical hazard, column (4) replaces the instrument, column (5) replaces both, and

TABLE A10. Non-Adjacent Instrument with Adjacent-Neighbor Damage Controls

	Baseline IV	Non-Adj IV	Non-Adj + Adj Ctrl
Panel A: Income, Employment, Housing			
Per capita income	+2.53*** (0.73)	+2.50*** (0.82)	+2.49*** (0.86)
Total income	+3.29*** (0.87)	+3.46*** (1.00)	+3.52*** (1.06)
Unemployment rate	−0.39*** (0.09)	−0.43*** (0.11)	−0.43*** (0.12)
House price index	+13.1*** (3.7)	+15.3*** (4.5)	+18.4*** (6.6)
Panel B: Establishments and Entrepreneurship			
Establishments	+2.39*** (0.62)	+2.50*** (0.64)	+2.58*** (0.68)
Business applications	+8.30*** (1.89)	+10.37*** (2.40)	+10.98*** (2.61)
Nonemployer receipts	+4.09*** (0.95)	+4.43*** (1.11)	+4.60*** (1.18)
Bus. app. rate	+0.67*** (0.15)	+0.86*** (0.19)	+0.92*** (0.21)
Panel C: Population and Migration			
Population	+0.76*** (0.27)	+0.97*** (0.35)	+1.03*** (0.38)
In-migration	+7.82*** (1.93)	+8.38*** (2.19)	+8.31*** (2.30)
Out-migration	+3.66*** (1.23)	+4.53*** (1.55)	+4.69*** (1.69)
Panel D: Local Government Finance			
Capital outlay	+36.8*** (11.6)	+40.4*** (12.6)	+41.0*** (13.0)
Debt outstanding	−15.0* (7.9)	−16.5** (8.2)	−16.6** (8.4)
Eff. property tax rate	−7.57*** (2.89)	−10.68*** (3.56)	−13.72** (5.58)
Muni offering yield	−0.30* (0.15)	−0.25* (0.15)	−0.33 (0.24)
Panel E: Banking and Credit			
Bank deposits	+3.02** (1.18)	+3.90*** (1.49)	+4.12** (1.61)
Bank net income	+6.55*** (2.43)	+7.53*** (2.83)	+7.64** (3.03)
NPL ratio	−0.24*** (0.08)	−0.27*** (0.10)	−0.27*** (0.10)
Panel F: Construction			
Gov. construction	+41.6*** (15.0)	+39.3*** (15.1)	+39.1** (15.4)
Constr. RE loans	+11.19*** (3.90)	+12.26*** (4.50)	+12.47*** (4.77)
Constr. establishments	+4.90*** (1.28)	+4.96*** (1.41)	+5.00*** (1.48)
Constr. earnings	+8.88*** (2.54)	+8.47*** (2.87)	+8.41*** (2.97)
N county-disasters	9,067	8,957	8,957
KP *F*	9–51	9–48	9–15

Notes: Each column reports the IV estimate of the effect of $100 per capita cumulative PA on each outcome. Log outcomes are multiplied by 100 for percentage interpretation; the unemployment rate is in percentage points; HPI in index points; muni yield in percentage points; business application rate per 1,000 population. "Baseline IV" uses the leave-one-out unweighted-mean peer damage instrument. "Non-Adj IV" excludes geographically adjacent peer counties from the instrument. "Non-Adj + Adj Ctrl" additionally controls for the mean damage per capita of adjacent peer counties interacted with a post-declaration indicator. All specifications include county and year fixed effects and FEMA + Storm quadratic own-damage controls. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A11. IV Estimates by Adjacent Damage Share

	Full	Q1 (low)	Q2	Q3	Q4 (high)
Income, Employment, and Housing					
Per capita income (log)	0.0253*** (0.0073)	0.0401 (0.0248)	0.0456*** (0.0127)	0.0025 (0.0092)	0.0094 (0.0122)
Total income (log)	0.0329*** (0.0087)	0.0559** (0.0281)	0.0587*** (0.0152)	0.0019 (0.0099)	−0.0029 (0.0129)
Unemployment rate	−0.390*** (0.093)	−1.128*** (0.247)	−0.283** (0.140)	0.063 (0.069)	−0.178 (0.131)
House price index	13.06*** (3.66)	15.78 (11.59)	29.11*** (7.31)	5.64 (4.05)	3.35 (7.16)
Establishments and Entrepreneurship					
Establishments (log)	0.0239*** (0.0062)	0.0379** (0.0165)	0.0410*** (0.0125)	0.0083 (0.0051)	0.0218 (0.0137)
Business apps (log)	0.0830*** (0.0189)	0.1855*** (0.0690)	0.1172*** (0.0344)	−0.0039 (0.0164)	0.0065 (0.0196)
Nonemployer receipts (log)	0.0409*** (0.0095)	0.0793*** (0.0250)	0.0652*** (0.0163)	0.0077 (0.0090)	0.0509*** (0.0191)
Bus. app. rate	0.671*** (0.152)	1.738*** (0.406)	1.043*** (0.311)	−0.024 (0.129)	−0.096 (0.189)
Population and Migration					
Population (log)	0.0067*** (0.0026)	0.0113 (0.0085)	0.0152*** (0.0049)	−0.0004 (0.0030)	−0.0043 (0.0045)
In-migration (log)	0.0782*** (0.0193)	0.2607*** (0.0648)	0.0732*** (0.0265)	−0.0387** (0.0170)	0.0081 (0.0218)
Out-migration (log)	0.0366*** (0.0123)	0.1125** (0.0519)	0.0430** (0.0187)	−0.0192* (0.0111)	−0.0353** (0.0159)
Local Government Finance					
Capital outlay (log)	0.3679*** (0.1160)	0.7893*** (0.1800)	0.1514 (0.1045)	0.0547 (0.0987)	0.1691 (0.1889)
Debt outstanding (log)	−0.1495* (0.0791)	−0.4270** (0.2003)	−0.1234 (0.1354)	−0.0727 (0.0910)	−0.0518 (0.1562)
Eff. ptax rate (log)	−0.0757*** (0.0289)	−0.0403 (0.0902)	−0.0859* (0.0454)	0.0024 (0.0318)	−0.0656 (0.0441)
Muni offering yield	−0.296* (0.152)	−0.264 (0.451)	−0.069 (0.162)	−0.001 (0.177)	−0.926 (0.657)
Banking and Credit					
Bank deposits (log)	0.0302** (0.0118)	0.0321 (0.0549)	0.0465*** (0.0151)	0.0212* (0.0119)	0.0100 (0.0156)
Bank net income (log)	0.0655*** (0.0243)	0.1314 (0.1073)	−0.0003 (0.0353)	0.0808** (0.0353)	0.0207 (0.0364)
NPL ratio	−0.0024*** (0.0008)	−0.0072** (0.0029)	−0.0021* (0.0011)	0.0001 (0.0009)	0.0003 (0.0013)
Construction					
Gov. construction (log)	0.4159*** (0.1502)	0.6972*** (0.2180)	0.0137 (0.1346)	0.1156 (0.1601)	0.4356 (0.2955)
Constr. RE loans (log)	0.1119*** (0.0390)	0.1284 (0.1733)	0.1419*** (0.0528)	0.0880** (0.0363)	0.1875** (0.0753)
Constr. establishments (log)	0.0490*** (0.0128)	0.0364 (0.0314)	0.0736*** (0.0262)	0.0312* (0.0180)	0.0629** (0.0251)
Constr. earnings (log)	0.0888*** (0.0254)	0.0949 (0.0694)	0.0853** (0.0415)	0.0225 (0.0223)	0.1081*** (0.0380)
N county-disasters	9,067	2,267	2,267	2,267	2,266
Median adj. share	0.115	<0.04	0.04–0.12	0.12–0.30	>0.30
KP *F*	9–51	9–58	4–26	10–16	4–19

Notes: Each cell reports the IV coefficient from the preferred specification (unweighted-mean LOO peer damage instrument, FEMA + Storm quadratic own-damage controls). Quartiles are defined over the share of total disaster damage originating from counties geographically adjacent to the focal county. Q1 counties have the lowest adjacent damage share (peers are predominantly non-adjacent); Q4 counties have the highest (peers are predominantly adjacent). Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

column (6) further drops the NOAA Storm Events control to identify the effect from physical hazard alone. Replacing the own-damage control leaves every coefficient essentially unchanged (column 3 against column 2), so the results are not an artifact of conditioning on a mismeasured control. Replacing the instrument with assessment-independent peer hazard preserves the income, employment, entrepreneurship, migration, and construction results, with a first stage that is in fact stronger than the FEMA instrument on this subsample - Kleibergen-Paap F-statistics of 40 to 90 for the income, employment, and migration outcomes against 8 to 12 for the FEMA instrument. House prices and the public finance outcomes are the exception: they hold under the FEMA instrument but attenuate under the physical instrument, which weights the flood- and hurricane-driven margin of compliance more heavily. Dropping the NOAA control entirely (column 6) changes nothing, confirming that no result depends on either FEMA-assessed damage measure.

TABLE A12. Robustness to Physical Damage Controls

	(1) Main paper Full sample	(2) Baseline Flood/hurr.	(3) FEMA inst. **Phys. control**	(4) **Physical inst.** FEMA control	(5) **Physical inst.** **Phys. control**	(6) **Physical inst.** **Phys., no NOAA**
Income, employment, and house prices						
Log per-capita income	0.025***	0.036***	0.031***	0.021***	0.026***	0.026***
	(0.007)	(0.009)	(0.007)	(0.003)	(0.004)	(0.004)
	[12]	[9]	[8]	[44]	[59]	[59]
Log total income	0.033***	0.048***	0.042***	0.024***	0.033***	0.033***
	(0.009)	(0.010)	(0.008)	(0.004)	(0.005)	(0.005)
	[12]	[9]	[8]	[44]	[59]	[59]
Unemployment rate (pp)	-0.390***	-0.418***	-0.337***	-0.467***	-0.397***	-0.393***
	(0.093)	(0.095)	(0.082)	(0.062)	(0.057)	(0.056)
	[12]	[9]	[8]	[44]	[59]	[59]
House price index (pts)	13.055***	19.586***	16.089***	5.395	7.671	7.777*
	(3.659)	(4.063)	(3.382)	(4.623)	(4.759)	(4.724)
	[29]	[55]	[45]	[36]	[62]	[63]
Establishments and entrepreneurship						

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Table A12, continued

	(1) Main paper Full sample	(2) Baseline Flood/hurr.	(3) FEMA inst. **Phys. control**	(4) **Physical inst.** FEMA control	(5) **Physical inst.** **Phys. control**	(6) **Physical inst.** **Phys., no NOAA**
Log establishments	0.024***	0.031***	0.026***	0.009***	0.014***	0.014***
	(0.006)	(0.007)	(0.006)	(0.003)	(0.003)	(0.003)
	[15]	[11]	[11]	[41]	[57]	[58]
Log business applications	0.083***	0.115***	0.096***	0.087***	0.099***	0.098***
	(0.019)	(0.022)	(0.018)	(0.012)	(0.013)	(0.013)
	[12]	[9]	[8]	[49]	[67]	[67]
Log sole-proprietor revenue	0.041***	0.053***	0.046***	0.020***	0.039***	0.039***
	(0.010)	(0.010)	(0.009)	(0.005)	(0.006)	(0.006)
	[15]	[11]	[11]	[41]	[57]	[58]
Business-application rate	0.671***	0.940***	0.783***	0.610***	0.775***	0.773***
	(0.152)	(0.167)	(0.143)	(0.126)	(0.126)	(0.126)
	[12]	[9]	[8]	[49]	[67]	[67]
Population and migration						
Log population	0.007***	0.013***	0.012***	0.007***	0.010***	0.010***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)

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Table A12, continued

	(1) Main paper Full sample	(2) Baseline Flood/hurr.	(3) FEMA inst. **Phys. control**	(4) **Physical inst.** FEMA control	(5) **Physical inst.** **Phys. control**	(6) **Physical inst.** **Phys., no NOAA**
	[13]	[10]	[9]	[43]	[58]	[59]
Log in-migration flow	0.078***	0.108***	0.092***	0.052***	0.046***	0.046***
	(0.019)	(0.020)	(0.018)	(0.009)	(0.009)	(0.009)
	[15]	[11]	[10]	[57]	[86]	[87]
Log out-migration flow	0.037***	0.049***	0.042***	0.023***	0.015**	0.015**
	(0.012)	(0.013)	(0.011)	(0.006)	(0.007)	(0.007)
	[15]	[11]	[10]	[57]	[86]	[87]
Construction sector						
Log government construction	0.416***	0.325**	0.274**	-0.008	0.149	0.146
	(0.150)	(0.144)	(0.128)	(0.082)	(0.104)	(0.101)
	[9]	[6]	[5]	[32]	[35]	[36]
Log construction RE loans	0.112***	0.067	0.064*	0.034	0.062***	0.062***
	(0.039)	(0.041)	(0.034)	(0.022)	(0.023)	(0.023)
	[13]	[9]	[9]	[58]	[84]	[85]
Log construction estab.	0.049***	0.059***	0.050***	0.028***	0.054***	0.054***

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Table A12, continued

	(1) Main paper Full sample	(2) Baseline Flood/hurr.	(3) FEMA inst. **Phys. control**	(4) **Physical inst.** FEMA control	(5) **Physical inst.** **Phys. control**	(6) **Physical inst.** **Phys., no NOAA**
	(0.013)	(0.014)	(0.012)	(0.008)	(0.009)	(0.009)
	[15]	[11]	[11]	[50]	[72]	[73]
Log construction earnings	0.089***	0.104***	0.090***	0.067***	0.097***	0.097***
	(0.025)	(0.028)	(0.022)	(0.015)	(0.016)	(0.015)
	[10]	[8]	[7]	[47]	[71]	[72]
Local government finance						
Log capital outlay	0.368***	0.297***	0.269**	-0.036	0.026	0.027
	(0.116)	(0.115)	(0.105)	(0.056)	(0.070)	(0.069)
	[12]	[7]	[7]	[29]	[40]	[41]
Log debt outstanding	-0.150*	-0.191***	-0.173***	-0.014	-0.032	-0.034
	(0.079)	(0.066)	(0.058)	(0.058)	(0.073)	(0.073)
	[10]	[6]	[6]	[35]	[47]	[49]
Log eff. property-tax rate	-0.076***	-0.080***	-0.064***	-0.059**	-0.070**	-0.067**
	(0.029)	(0.029)	(0.022)	(0.027)	(0.031)	(0.031)
	[51]	[54]	[46]	[26]	[47]	[49]

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Table A12, continued

	(1) Main paper Full sample	(2) Baseline Flood/hurr.	(3) FEMA inst. **Phys. control**	(4) **Physical inst.** FEMA control	(5) **Physical inst.** **Phys. control**	(6) **Physical inst.** **Phys., no NOAA**
Muni offering yield (pp)	-0.296*	-0.317**	-0.263**	-0.155	-0.174	-0.170
	(0.152)	(0.155)	(0.132)	(0.106)	(0.119)	(0.117)
	[17]	[15]	[19]	[13]	[15]	[14]
Sample	Full	Flood/hurricane subsample				
Instrument (peer, LOO)	FEMA PDA	FEMA PDA	FEMA PDA	**Physical**	**Physical**	**Physical**
Own-damage control	FEMA PDA	FEMA PDA	**Physical**	FEMA PDA	**Physical**	**Physical**
NOAA Storm control	Yes	Yes	Yes	Yes	Yes	**No**
County + year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	County					
Observations	77,199	63,534	63,534	63,534	63,534	63,534

Notes: The table reports instrumental-variables estimates of the effect of cumulative FEMA Public Assistance per capita on each outcome, scaled to reflect $100 per capita. Each specification instruments cumulative PA with the within-disaster, unweighted leave-one-out mean of peer counties' damage interacted with the post-disaster indicator, as in equations (1) and (2); the columns differ in the sample and in the damage measure used to form the instrument and the own-damage control. Column (1) reproduces the main-paper estimate, which uses FEMA Preliminary Damage Assessment (PDA) per-capita damage for both the peer instrument and the own-damage control, on the full sample of disasters. Columns (2)–(6) restrict to the flood- and hurricane-classified disasters for which physically modeled hazard intensity is available, holding the sample fixed

so the columns are comparable: column (2) repeats the baseline specification on this subsample; column (3) replaces the own-damage control with physical hazard intensity; column (4) replaces the instrument; column (5) replaces both; column (6) additionally drops the NOAA Storm Events control, identifying the effect from physically modeled hazard alone. Physical hazard intensity combines the GloFAS river-discharge flood return period (Farkas and Kim) with modeled hurricane wind from the Willoughby model applied to NOAA HURDAT2 best-track data, and is constructed independently of FEMA's damage assessment. All specifications include county and calendar-year fixed effects. Columns (1)–(5) additionally include a quadratic control for own NOAA Storm Events damage; column (6) omits it. The own-damage assessment control reported in the table enters as a quadratic: it is FEMA PDA per-capita damage in columns (1), (2), and (4), and physical hazard intensity (quadratics in GloFAS flood return period and hurricane wind) in columns (3), (5), and (6). Standard errors clustered by county in parentheses; Kleibergen–Paap cluster-robust first-stage F-statistics in brackets. The reported number of observations is for the per-capita income specification; the estimation sample varies across outcomes. Sources: FEMA PDA, OpenFEMA, GloFAS, NOAA HURDAT2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix L. Within-Disaster Identification

The crossing in Appendix K would be undermined if the FEMA assessment and the physical measures erred together - if some events were systematically mismeasured by a rapid field assessment, a hydrological model, and a wind model at the same time, in a way correlated with the local economy. Because any such factor is a property of the disaster, shared by all of its counties, disaster fixed effects difference it out: they identify the effect purely from variation across counties *within the same disaster*. The cost is power - the leave-one-out instrument has little within-disaster variation - which is exactly why this test requires the physical instrument, whose first stage is several times stronger than the FEMA instrument's.

Table A13 adds disaster fixed effects to the physical specifications. The first stage holds up: the physical instrument retains Kleibergen-Paap F-statistics near 30 for the annual outcomes, where the FEMA instrument collapses to roughly 5. Income, total income, unemployment, establishments, business applications, sole-proprietor revenue, population, and the entire construction sector survive, with magnitudes if anything larger than the baseline. House prices remain positive but become imprecise, and in-migration is identified by cross-disaster rather than within-disaster variation. The census-year government-finance outcomes have too little within-disaster variation to support disaster fixed effects ($F < 12$) and are not identified in columns (3)–(4). For the core real-activity results, then, the effect is present even when the comparison is restricted to counties hit by the same disaster, which leaves no room for a disaster-level confound - measurement-driven or otherwise.

TABLE A13. Within-Disaster Identification: Robustness to Disaster-Level Confounds

	(1) FEMA inst. FEMA control	(2) **Physical inst. Phys. control**	(3) **Physical inst.** FEMA control **+ disaster FE**	(4) **Physical inst. Phys. control + disaster FE**
Income, employment, and house prices				
Log per-capita income	0.036***	0.026***	0.044***	0.044***

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Table A13, continued

	(1) FEMA inst. FEMA control	(2) **Physical inst. Phys. control**	(3) **Physical inst.** FEMA control **+ disaster FE**	(4) **Physical inst. Phys. control + disaster FE**
	(0.009)	(0.004)	(0.007)	(0.007)
	[9]	[59]	[30]	[30]
Log total income	0.048***	0.033***	0.046***	0.045***
	(0.010)	(0.005)	(0.008)	(0.008)
	[9]	[59]	[30]	[30]
Unemployment rate (pp)	-0.418***	-0.397***	-0.391***	-0.386***
	(0.095)	(0.057)	(0.087)	(0.086)
	[9]	[59]	[30]	[30]
House price index (pts)	19.586***	7.671	8.529	8.306
	(4.063)	(4.759)	(6.265)	(6.141)
	[55]	[62]	[22]	[22]
Establishments and entrepreneurship				
Log establishments	0.031***	0.014***	0.020***	0.019***
	(0.007)	(0.003)	(0.006)	(0.006)
	[11]	[57]	[28]	[28]
Log business applications	0.115***	0.099***	0.059***	0.058***
	(0.022)	(0.013)	(0.017)	(0.017)
	[9]	[67]	[34]	[34]
Log sole-proprietor revenue	0.053***	0.039***	0.065***	0.063***
	(0.010)	(0.006)	(0.011)	(0.011)
	[11]	[57]	[28]	[28]
Business-application rate	0.940***	0.775***	0.331**	0.327**
	(0.167)	(0.126)	(0.149)	(0.146)
	[9]	[67]	[34]	[34]

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Table A13, continued

	(1) FEMA inst. FEMA control	(2) **Physical inst. Phys. control**	(3) **Physical inst.** FEMA control **+ disaster FE**	(4) **Physical inst. Phys. control + disaster FE**
Population and migration				
Log population	0.013***	0.010***	0.011***	0.010***
	(0.003)	(0.002)	(0.004)	(0.004)
	[10]	[58]	[29]	[29]
Log in-migration flow	0.108***	0.046***	0.006	0.007
	(0.020)	(0.009)	(0.012)	(0.012)
	[11]	[86]	[42]	[42]
Log out-migration flow	0.049***	0.015**	-0.035***	-0.035***
	(0.013)	(0.007)	(0.012)	(0.011)
	[11]	[86]	[42]	[42]
Construction sector				
Log government construction	0.325**	0.149	0.481*	0.450*
	(0.144)	(0.104)	(0.260)	(0.249)
	[6]	[35]	[8]	[8]
Log construction RE loans	0.067	0.062***	0.147***	0.143***
	(0.041)	(0.023)	(0.038)	(0.037)
	[9]	[84]	[39]	[38]
Log construction estab.	0.059***	0.054***	0.097***	0.095***
	(0.014)	(0.009)	(0.017)	(0.017)
	[11]	[72]	[35]	[34]
Log construction earnings	0.104***	0.097***	0.082***	0.079***
	(0.028)	(0.016)	(0.025)	(0.025)
	[8]	[71]	[27]	[26]
Local government finance				

continued on next page

Table A13, continued

	(1) FEMA inst. FEMA control	(2) **Physical inst. Phys. control**	(3) **Physical inst.** FEMA control **+ disaster FE**	(4) **Physical inst. Phys. control + disaster FE**
Log capital outlay	0.297***	0.026	-0.032	-0.039
	(0.115)	(0.070)	(0.142)	(0.140)
	[7]	[40]	[11]	[12]
Log debt outstanding	-0.191***	-0.032	0.149	0.136
	(0.066)	(0.073)	(0.187)	(0.175)
	[6]	[47]	[9]	[10]
Log eff. property-tax rate	-0.080***	-0.070**	-0.071	-0.067
	(0.029)	(0.031)	(0.080)	(0.076)
	[54]	[47]	[4]	[4]
Muni offering yield (pp)	-0.317**	-0.174	-0.160	-0.157
	(0.155)	(0.119)	(0.187)	(0.182)
	[15]	[15]	[5]	[5]
Instrument (peer, LOO)	FEMA PDA	**Physical**	**Physical**	**Physical**
Own-damage control	FEMA PDA	**Physical**	FEMA PDA	**Physical**
Disaster FE	No	No	**Yes**	**Yes**
County + year FE	Yes	Yes	Yes	Yes
Clustering		County		
Observations	63,534	63,534	63,534	63,534

Notes: Instrumental-variables estimates of the effect of cumulative Public Assistance per capita on each outcome, scaled to $100 per capita, on the flood- and hurricane-classified disasters for which physically modeled hazard intensity is available. Column (1) is the baseline (FEMA Preliminary Damage Assessment instrument and own-damage control). Column (2) uses the assessment-independent physical instrument and control - the GloFAS flood return period (Farkas and Kim, 2025) and modeled hurricane wind (Willoughby et al., 2006). Columns (3) and (4) add disaster fixed effects, so the effect is identified purely from variation across counties *within the same disas-*

ter, which differences out any disaster-level confound, including measurement error common to both damage measures. The physical instrument retains a strong first stage under disaster fixed effects (Kleibergen–Paap F in brackets) where the FEMA instrument does not. The census-year government-finance outcomes are too sparse to support disaster fixed effects ($F < 12$) and are not identified in columns (3)–(4). Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix M. Mortality

Table A14 tests whether PA affects mortality rates using the CDC Compressed Mortality File (1999–2016). All three measures - the mortality rate per 100,000, log deaths, and the inverse hyperbolic sine of the mortality rate - are insignificant under both the baseline and non-adjacent instruments, with clean pre-trends. The point estimates are negative but imprecise.

TABLE A14. Mortality: OLS and IV Estimates

	Mortality rate (per 100K)	Log deaths	Asinh mortality rate
Panel A: OLS			
PA per cap (×100)	0.156 (0.613)	−0.0003 (0.0005)	0.0001 (0.0005)
Panel B: IV (unweighted)			
PA per cap (×100)	−9.900 (6.698)	−0.0027 (0.0051)	−0.0076 (0.0052)
Panel C: IV non-adjacent			
PA per cap (×100)	−11.207 (7.482)	−0.0024 (0.0059)	−0.0080 (0.0059)
N (panel obs.)	47,284	47,277	47,284
KP F (Panel B)	36	36	36
KP F (Panel C)	34	34	34

Notes: Each column reports the effect of $100 per capita cumulative FEMA Public Assistance on mortality outcomes from the CDC Compressed Mortality File (1999–2016). Mortality rate is deaths per 100,000 population. All specifications include county and year fixed effects and FEMA + Storm quadratic own-damage controls. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix N. Banking and Credit

Cortés and Strahan (2017) document that financially integrated banks reallocate capital toward disaster-affected counties, expanding lending in struck areas by drawing from non-disaster branches. Does PA amplify this private credit response,

or substitute for it? Table A15 reports the IV effects of PA on three measures of the local banking system: county-level deposits, county-allocated bank net income, and the nonperforming loan ratio.[25]

An extra $100 per capita of public assistance raises county-level bank deposits by 3.0%, county-allocated bank net income by 6.6%, and lowers the nonperforming loan ratio - noncurrent loans as a share of total loans - by 0.24 percentage points off a 1.5% baseline, a 16% reduction. All three outcomes have clean reduced-form pre-trends (Figure A5). Anderson-Rubin confidence intervals exclude zero for net income and the NPL ratio; the deposits interval marginally includes zero. The lower NPL ratio reflects the income and employment gains in Section 4.1 improving borrower repayment capacity across existing loan portfolios.

PA does not expand aggregate credit. Total bank lending is unchanged ($p = 0.38$), and the loan-to-deposit ratio does not move ($p = 0.90$). PA shifts the *composition* of the loan book toward reconstruction lending - construction and land-development loans rise by 11%, reported in Section 4.4 - but does not expand its size. The deposit increase mirrors the income gain in Table 3; the construction-lending increase finances the reconstruction activity. The banking system is a conduit for PA's effects on the local economy, not an amplifier of them.

Appendix O. Mitigation versus Repair

FEMA Public Assistance finances two distinct kinds of work. Most obligations fund repair and replacement of damaged public infrastructure under the seven eligible work categories (A–G). A smaller slice funds Section 406 hazard-mitigation add-ons: upgrades to repaired facilities - stronger materials, elevation, wind-resistant construction - that reduce the probability or severity of losses in future disasters. OpenFEMA records the mitigation portion of each project separately. In the analysis sample it accounts for $8.7 billion, or 6.8% of total federal obligations, and is concentrated in permanent-work categories C–G (Section 406 mitigation attaches to a repair project; Categories A and B, debris removal and emergency protective

[25] Column (1) uses county-level deposit totals from the FDIC Summary of Deposits (1994–2023). Columns (2)–(3) use bank-level Call Report data allocated to counties in proportion to each bank's branch deposits in the Summary of Deposits, following Gilje et al. (2016) and Cortés and Strahan (2017). A bank with 60% of its deposits in county c contributes 60% of its total loans, net income, and noncurrent loans to that county's aggregate.

TABLE A15. Effects of FEMA Public Assistance on Banking and Credit

	Deposits (1)	Net Income (2)	NPL Ratio (3)
Panel A: OLS			
$100 cum.	0.0020***	0.0023	-0.0002*
PA/capita	(0.0006)	(0.0017)	(0.0001)
Panel B: IV			
$100 cum.	0.0302**	0.0655***	-0.0024***
PA/capita	(0.0118)	(0.0243)	(0.0008)
AR 95% CI	[-0.0053, 0.0508]	[0.0031, 0.1174]	[-0.0045, -0.0008]
KP F	13	12	13
Outcome mean	$2.6B	—	—
Observations	75,069	72,567	75,042
Source	FDIC SOD	FDIC Call	FDIC Call
County + year FE	Yes	Yes	Yes
Damage controls	FEMA + Storm (quadratic)		
Clustering	County	County	County

Notes: Estimates of the impact of additional PA per capita on banking and credit outcomes. Coefficients are scaled to reflect the effect of $100 per capita in cumulative PA. The estimating equations are (1) and (2). Panel A reports OLS estimates. Panel B reports IV estimates. AR 95% CI denotes the Anderson-Rubin weak-instrument-robust confidence interval. KP F is the Kleibergen-Paap cluster-robust first-stage F-statistic. Data sources: county-level bank deposits from FDIC Summary of Deposits (1994–2023); net income and the noncurrent loan ratio (noncurrent loans, defined as those 90+ days past due or in nonaccrual status, divided by total loans) from FDIC Call Reports, allocated to counties using branch deposit share weights. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

measures, have essentially zero mitigation content).

I ask two questions. First, does the instrument predict mitigation obligations? I split cumulative PA per capita into a mitigation component and a repair component and regress each on the instrument. The first stage on repair is essentially identical to the first stage on total PA: coefficient 0.108, Kleibergen-Paap $F = 12$ unweighted and 47 population-weighted, statistically indistinguishable from the total-PA first stage. The first stage on mitigation is flat: coefficient 0.003, KP $F \approx 1.2$ unweighted and 2.7 population-weighted, with a t-statistic below 2 in both cases. The correlation between the mitigation and repair components in the panel is only 0.20, confirming that they carry independent variation; the instrument moves one and not the other. This is expected: peer-damage-driven crowd-out operates at the scale of the total PA budget - on the repair work that dominates it - not on the comparatively small mitigation set-asides that enter later in the project lifecycle.

Second, does treating repair as the endogenous regressor change any conclusions? Table A16 re-estimates all 22 outcomes from the main results tables and the banking appendix under two specifications: the baseline, which uses total cumulative PA, and a repair-only specification that substitutes the repair component. All other elements - instrument, fixed effects, damage controls, clustering, sample - are unchanged. Every coefficient is 2.3% to 4.8% larger in absolute value under the repair-only specification, with a median increase of 3.9%. Signs, significance, and first-stage strength are unchanged for all 22 outcomes. The uniform magnitude of the rescaling reflects the mechanical fact that repair is 93% of the denominator the instrument shifts: dividing the same reduced-form impact by a slightly smaller treatment yields a slightly larger IV coefficient. Nothing substantive changes.

The implication is that the main-paper coefficients should be read as the effect of repair-PA per dollar. Section 406 mitigation spending is a small and independent component of federal obligations whose causal effect is not identified by this instrument. Any welfare claims in the paper apply to reconstruction spending, not to hazard mitigation.

Appendix P. Alternative Population Measures

The population result in Table 5 uses the Census SAIPE poverty universe as a population measure (1997–2023). Table A17 compares this estimate against two alter-

TABLE A16. Re-estimating Main Outcomes with Non-Mitigation (Repair) PA Only

	IV (all PA) (1)	IV (repair only) (2)	% change (3)
Income, Employment, Housing (*Table 3*)			
Per capita income (log)	0.0253*** (0.0073)	0.0262*** (0.0076)	+3.6%
Total income (log)	0.0329*** (0.0087)	0.0340*** (0.0089)	+3.6%
Unemployment rate (pp)	-0.3904*** (0.0929)	-0.4043*** (0.0949)	+3.6%
House price index	13.06*** (3.659)	13.58*** (3.779)	+4.0%
Establishments and Entrepreneurship (*Table 4*)			
Establishments (log)	0.0239*** (0.0062)	0.0251*** (0.0065)	+4.8%
Business applications (log)	0.0830*** (0.0189)	0.0859*** (0.0194)	+3.5%
Nonemployer receipts (log)	0.0409*** (0.0095)	0.0429*** (0.0100)	+4.8%
Bus. app. rate (per 1,000)	0.6710*** (0.1524)	0.6947*** (0.1561)	+3.5%
Population and Migration (*Table 5*)			
Population (log, SAIPE)	0.0067*** (0.0026)	0.0070*** (0.0027)	+4.2%
In-migration returns (log)	0.0782*** (0.0193)	0.0818*** (0.0201)	+4.6%
Out-migration returns (log)	0.0366*** (0.0123)	0.0384*** (0.0128)	+4.7%
Local Public Finance (*Table 8*)			
Capital outlay (log)	0.3679*** (0.1160)	0.3815*** (0.1187)	+3.7%
Debt outstanding (log)	-0.1495* (0.0791)	-0.1530* (0.0807)	+2.3%
Eff. property tax rate (log)	-0.0757*** (0.0289)	-0.0783*** (0.0299)	+3.5%
Muni offering yield (pp)	-0.2964* (0.1516)	-0.3074* (0.1573)	+3.7%
Banking and Credit (*Table A15*)			
Deposits (log)	0.0302** (0.0118)	0.0314** (0.0124)	+4.2%
Bank net income (log)	0.0655*** (0.0243)	0.0682*** (0.0253)	+4.2%
NPL ratio	-0.0024*** (0.0008)	-0.0025*** (0.0008)	+4.1%
Construction (*Table 6*)			
Gov. construction (log)	0.4159*** (0.1502)	0.4305*** (0.1534)	+3.5%
Constr. RE loans (log)	0.1119*** (0.0390)	0.1164*** (0.0407)	+4.1%
Constr. establishments (log)	0.0490*** (0.0128)	0.0514*** (0.0133)	+4.8%
Constr. earnings (log)	0.0888*** (0.0254)	0.0911*** (0.0259)	+2.6%
N (panel obs.)	77,667	77,667	
KP F	9–51	9–52	

Notes: Each row re-estimates one main-paper outcome under two endogenous regressors. Column (1) uses cumulative federal Public Assistance per capita - the baseline specification in Tables 3–6. Column (2) uses only the non-mitigation ("repair") component, defined as federal share obligated minus the Section 406 mitigation amount reported at the project level in OpenFEMA. Column (3) reports the percentage change in the point estimate relative to column (1). Coefficients are scaled to the effect of $100 per capita in cumulative treatment. All specifications include county and year fixed effects and FEMA + Storm quadratic own-damage controls. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

natives: the BEA CAINC1 resident population (1969–2023) and the CDC WONDER Compressed Mortality File denominator (1999–2016). All three sources yield positive and significant effects of PA on population, with coefficients ranging from +0.50% to +0.76% per $100/capita. I use SAIPE in the main tables because it has clean reduced-form pre-trends at all pre-periods ($k = -4, -3, -2$). The BEA measure, which has the longest time series, fails pre-trends at all three horizons ($p < 0.01$). The CDC measure is marginal ($k = -4$: $p = 0.046$) and covers fewer years.

TABLE A17. Population: Alternative Data Sources

	SAIPE (main)	BEA	CDC WONDER
PA per cap (×100)	0.0067*** (0.0026)	0.0076*** (0.0027)	0.0050*** (0.0019)
N (panel obs.)	75,418	77,199	47,740
KP F	13	12	36

Notes: Each column reports the IV estimate of the effect of $100 per capita cumulative FEMA Public Assistance on log population, using an alternative population source. SAIPE population is derived from the Census Small Area Income and Poverty Estimates poverty universe (1997–2023); BEA population is from BEA CAINC1 (1969–2023); CDC population is from the CDC WONDER Compressed Mortality File denominator (1999–2016). All specifications include county and year fixed effects and FEMA + Storm quadratic own-damage controls. Standard errors clustered by county in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Q. Welfare Model Details

This appendix provides the formal details underlying the welfare model in Section 6: the complete equilibrium definition, existence and uniqueness, derivations of the comparative statics, proofs that all equilibrium responses are signed under a single regularity condition, and sensitivity tables for the welfare decomposition.

Q.1. Setup

I briefly restate the model primitives. There are two locations: a disaster-affected county i and the rest of the country o. County i has a pre-disaster public capital stock $\bar{K}_i^g$, of which the disaster destroys ΔK^g units. The federal government provides PA_i dollars, restoring public capital to $K_i^g = \bar{K}_i^g - \Delta K^g + \alpha \cdot PA_i$, where α is the restoration efficiency. The outside location o is unaffected.

Workers.. A unit mass of workers chooses locations to maximize indirect utility:

$$V_j^\nu = w_j - \left(1 + \frac{\tau_j}{\rho}\right) r_j + B_j + \epsilon_j^\nu,$$

where w_j is the wage, r_j is the flow rent, τ_j is the property tax rate on house prices $P_j = r_j/\rho$, $B_j = b(K_j^g)$ is a concave amenity function of public capital, and ϵ_j^ν is i.i.d. Type I extreme value with scale $\kappa > 0$. Location shares follow the logit:

$$\frac{N_i}{N} = \frac{\exp(\Lambda_i/\kappa)}{\exp(\Lambda_i/\kappa) + \exp(\bar{\Lambda}_o/\kappa)},$$

where $\Lambda_j \equiv w_j - (1 + \tau_j/\rho)\, r_j + B_j$ is the location value and $\bar{\Lambda}_o$ is the fixed outside option.

Firms.. Competitive firms produce $Y_j = (K_j^g)^\beta N_j^{1-\beta}$, paying wages equal to the marginal product of labor: $w_j = (1-\beta)(K_j^g/N_j)^\beta$.

Housing.. Isoelastic supply $H_j = \bar{H}_j \cdot r_j^\eta$ with market clearing $H_j = N_j$ gives $r_j = (N_j/\bar{H}_j)^{1/\eta}$. Landlord profits are $\Pi_j^H = (1 - \tau_j/\rho)\, r_j \cdot N_j - C(N_j)$, where $C(N_j)$ is the cost function dual to the supply curve.

Local government.. The county levies property taxes to finance expenditure and service pre-existing debt:

$$\tau_i \cdot \frac{r_i}{\rho} \cdot N_i + PA_i + D_i = G_i + (1 + i_b)\, D_{i,0},$$

where G_i is total expenditure, i_b is the exogenous borrowing rate, $D_{i,0}$ is pre-existing debt, and D_i is new debt issued.

Q.2. Equilibrium definition

Since county i is small relative to o, I treat the outside option as fixed.

DEFINITION A1. *Given PA_i and ΔK^g, an **equilibrium** is a vector $(N_i, w_i, r_i, \tau_i, D_i)$ satisfying:*

a. *Labor market clearing: $w_i = (1-\beta)(K_i^g/N_i)^\beta$, where $K_i^g = \bar{K}_i^g - \Delta K^g + \alpha \cdot PA_i$.*
b. *Housing market clearing: $r_i = (N_i/\bar{H}_i)^{1/\eta}$.*

c. *Spatial equilibrium:*

$$N_i = N \cdot \frac{\exp\left[\left(w_i - (1+\tau_i/\rho)\, r_i + B_i(K_i^g)\right)/\kappa\right]}{\exp\left[\left(w_i - (1+\tau_i/\rho)\, r_i + B_i(K_i^g)\right)/\kappa\right] + \exp\left[\bar{\Lambda}_o/\kappa\right]}. \tag{A1}$$

d. *Government budget:* $\tau_i \cdot (r_i/\rho) \cdot N_i + PA_i + D_i = G_i + (1+i_b)\, D_{i,0}$.

e. *Optimal fiscal policy:* $\mathrm{DWL}'(\tau_i) = i_b$.

Conditions (1) and (2) express w_i and r_i as functions of N_i. Conditions (4) and (5) jointly determine τ_i and D_i given (N_i, r_i). Condition (3) then pins down N_i as a fixed point.

Q.3. Existence and uniqueness

The equilibrium can be characterized as a fixed point in N_i. The FOC $\mathrm{DWL}'(\tau_i) = i_b$ pins down τ_i as a function of the tax base: given a DWL function of the form $\mathrm{DWL}(\tau) = \frac{1}{2}\varepsilon\,\tau^2/(1-\tau)^2 \cdot \mathcal{B}$, the FOC determines τ_i given i_b and $\mathcal{B}_i = (r_i/\rho) \cdot N_i$. The budget constraint then determines D_i residually. Substituting $w_i(N_i)$, $r_i(N_i)$, and $\tau_i(N_i)$ into the migration equation (A1) yields a single equation $N_i = \Phi(N_i)$.

I verify that Φ is a contraction. As N_i increases:

- Wages fall: $\partial w_i/\partial N_i = -\beta w_i/N_i < 0$ (diminishing marginal product of labor).
- Rents rise: $\partial r_i/\partial N_i = r_i/(\eta N_i) > 0$ (housing demand pressure).
- The tax base $(r_i/\rho) \cdot N_i$ rises (more people and higher house prices), which *lowers* τ_i via the FOC (the marginal DWL falls as the base expands, so the government can reduce τ).

The first two effects reduce location value, ensuring Φ is eventually decreasing. The third (tax-base feedback) partially offsets by lowering taxes, which attracts further in-migration. The net feedback coefficient is proportional to τ_i/ρ - the tax burden as a fraction of house price. For US counties, $\tau \approx 1.7\%$ and $\rho \approx 5\%$, so $\tau/\rho \approx 0.34$, far below the instability threshold of 1.

More precisely, the denominator of the population response (derived in the next subsection) is:

$$\mathcal{D} = 1 + \frac{1}{\kappa}\left[\beta\, w_i + \frac{r_i}{\eta} - \frac{\tau_i r_i}{\rho}\right]. \tag{A2}$$

The condition $\mathcal{D} > 0$ is sufficient for the fixed-point map Φ to be a contraction

(the derivative $\Phi'(N_i) < 1$). Since $\beta w_i > 0$ and $r_i/\eta > 0$, a sufficient condition is $\tau_i < \rho$ - the property tax rate is less than the capitalization rate. This holds for all US counties: at $\tau/\rho \approx 0.34$, the stabilizing forces (wage compression and rent increases) dominate the destabilizing feedback (tax-base expansion) by a wide margin.

A unique equilibrium therefore exists for any $\tau_i < \rho$.

Q.4. Comparative statics of PA

Q.4.1. Direct effects (holding N_i fixed)

An increase in PA_i has three direct effects on the location value $\Lambda_i = w_i - (1 + \tau_i/\rho)\, r_i + B_i$:

Productivity. Higher K_i^g raises the marginal product of labor:

$$\left.\frac{dw_i}{dPA}\right|_N = \beta(1-\beta)\left(\frac{K_i^g}{N_i}\right)^{\beta-1}\frac{\alpha}{N_i} = \frac{\beta\, w_i\, \alpha}{K_i^g} > 0. \tag{A3}$$

Amenity. Higher K_i^g raises the local amenity:

$$\left.\frac{dB_i}{dPA}\right|_N = b'(K_i^g)\cdot\alpha > 0. \tag{A4}$$

Fiscal relief. PA relaxes the budget constraint. Holding N_i and r_i fixed, an additional dollar of PA reduces the government's financing need by one dollar. At the optimum (FOC: $\mathrm{DWL}'(\tau) = i_b$), the government reduces τ until the marginal DWL again equals the borrowing rate. For the standard Harberger DWL, the direct effect on τ is:

$$\left.\frac{d\tau_i}{dPA}\right|_N = -\frac{\rho}{r_i \cdot N_i} < 0. \tag{A5}$$

One PA dollar reduces each resident's annual tax bill by $1/N_i$ dollars.[26]

There is no direct effect on rents (housing depends only on population). Collect-

[26] The tax reduction $d\tau \cdot P_i = d\tau \cdot r_i/\rho = [\rho/(r_i N_i)] \cdot r_i/\rho = 1/N_i$.

ing terms, the total direct effect on location value is:

$$\left.\frac{d\Lambda_i}{dPA}\right|_N = \frac{\beta\, w_i\, \alpha}{K_i^g} + b'(K_i^g)\,\alpha + \frac{1}{N_i}. \tag{A6}$$

Q.4.2. General equilibrium population response

Workers respond to the improved location value by migrating in. For a small county ($N_i/N \approx 0$), the logit structure implies $d\ln N_i/dPA \approx (1/\kappa)\cdot d\Lambda_i/dPA$ at fixed wages, rents, and taxes. In general equilibrium, in-migration changes all three, requiring the full system to be solved simultaneously.

Totally differentiate the location value with respect to PA, allowing N_i to adjust. Using $d\ln w = (\beta\,\alpha/K_i^g)\,dPA - \beta\, d\ln N$ (from the wage equation), $d\ln r = (1/\eta)\, d\ln N$ (from housing clearing), and the budget constraint for $d\tau$:

$$\frac{d\Lambda_i}{dPA} = \left.\frac{d\Lambda_i}{dPA}\right|_N - \beta\, w_i \frac{d\ln N_i}{dPA} - \frac{(1+\tau_i/\rho)}{\eta}\, r_i \frac{d\ln N_i}{dPA} + \frac{\tau_i r_i}{\rho}\left(1+\frac{1}{\eta}\right)\frac{d\ln N_i}{dPA}. \tag{A7}$$

The first additional term $(-\beta w_i\, d\ln N)$ is wage compression from diminishing returns. The second $(-(1+\tau/\rho) r_i\, d\ln N/\eta)$ is the rent increase, including its tax component. The third is the tax-base feedback: in-migration expands the base through more housing units ($N_i \uparrow$) and higher rents ($r_i \uparrow$), allowing lower τ.

Using $d\ln N_i/dPA = (1/\kappa)\cdot d\Lambda_i/dPA$ and solving for $d\ln N_i/dPA$:

$$\frac{d\ln N_i}{dPA} = \frac{(1/\kappa)\cdot \left.\dfrac{d\Lambda_i}{dPA}\right|_N}{1 + \dfrac{1}{\kappa}\left[\beta\, w_i + \dfrac{(1+\tau_i/\rho)}{\eta}\, r_i - \dfrac{\tau_i\, r_i}{\rho}\left(1+\dfrac{1}{\eta}\right)\right]}. \tag{A8}$$

Expanding and simplifying the denominator (the $\tau_i r_i/(\rho\eta)$ terms cancel):

$$\mathcal{D} = 1 + \frac{1}{\kappa}\left[\beta\, w_i + \frac{r_i}{\eta} - \frac{\tau_i r_i}{\rho}\right], \tag{A9}$$

which is equation (A2). The three terms in brackets represent:

- βw_i: wage compression (standard).
- r_i/η: rent increase from inelastic housing supply (standard).
- $-\tau_i r_i/\rho$: tax-base feedback (*new*). Negative in the denominator, so it *amplifies* the population response.

The fiscal feedback multiplier - the ratio of the population response with the fiscal block to the response without it - is:

$$\mathcal{M} = \frac{1 + (1/\kappa)[\beta w_i + r_i/\eta]}{1 + (1/\kappa)[\beta w_i + r_i/\eta - \tau_i r_i/\rho]} > 1.$$

At $\tau/\rho \approx 0.34$ and the calibrated κ, w, r, and $\eta \approx 0.16$, this implies amplification of roughly 1.6% at the central estimate, and 1–3% across the γ–ρ grid. The feedback is modest because housing supply is highly inelastic: the rent-crowding term r/η dominates the denominator, leaving little scope for the tax-base feedback to operate.

Q.4.3. Downstream equilibrium responses

Given $d \ln N_i/dPA$, all other responses follow:

Wages:

$$\frac{d \ln w_i}{dPA} = \frac{\beta \, \alpha}{K_i^g} - \beta \, \frac{d \ln N_i}{dPA}. \tag{A10}$$

Rents:

$$\frac{d \ln r_i}{dPA} = \frac{1}{\eta} \, \frac{d \ln N_i}{dPA}. \tag{A11}$$

Tax rate:

$$\frac{d\tau_i}{dPA} = -\frac{\rho}{r_i N_i} - \tau_i \left(\frac{d \ln r_i}{dPA} + \frac{d \ln N_i}{dPA} \right). \tag{A12}$$

The total tax response decomposes into direct fiscal relief (first term) and the endogenous tax-base expansion (second term). Both are negative: PA unambiguously lowers the effective tax rate.

Establishments (proportional to output):

$$\frac{d \ln M_i}{dPA} = \frac{d \ln Y_i}{dPA} = \frac{\beta \, \alpha}{K_i^g} + (1 - \beta) \, \frac{d \ln N_i}{dPA}. \tag{A13}$$

Q.5. Signing the equilibrium responses

PROPOSITION A1. *Suppose $\tau_i < \rho$ (the property tax rate is less than the capitalization rate). Then a marginal increase in PA_i has the following effects:*

(a) *Population increases: $d \ln N_i / dPA > 0$.*
(b) *Rents increase: $d \ln r_i / dPA > 0$.*
(c) *The tax rate decreases: $d\tau_i / dPA < 0$.*
(d) *Debt decreases: $dD_i / dPA < 0$.*
(e) *Establishments increase: $d \ln M_i / dPA > 0$.*
(f) *Wages increase if and only if $d \ln N_i / dPA < \alpha / K_i^g$ - the population inflow is smaller than the percentage increase in public capital.*

The condition $\tau_i < \rho$ requires the property tax rate to be less than the capitalization rate, which must hold for homeownership to be viable (otherwise the tax bill would exceed the rental value). For US counties, $\tau/\rho \approx 0.34$.

PROOF. *Part (a).* From equation (A8), $d \ln N_i / dPA$ has the sign of $d\Lambda_i / dPA|_N / \mathcal{D}$. The numerator is strictly positive: all three direct effects in (A6) are positive. The denominator $\mathcal{D}$ from (A9) is positive if $\beta w_i + r_i/\eta > \tau_i r_i/\rho$. Since $\beta w_i > 0$, it suffices that $1/\eta > \tau_i/\rho$. Under $\tau_i < \rho$, this holds for any $\eta \leq 1$. For $\eta > 1$, the additional slack from βw_i ensures $\mathcal{D} > 0$: the required condition is $\tau_i/\rho < 1/\eta + \beta w_i / r_i$, and the right-hand side exceeds 1 for any $\eta > 0$.

Part (b). From (A11): $d \ln r_i / dPA = (1/\eta)\, d \ln N_i / dPA > 0$ since $\eta > 0$ and $d \ln N > 0$.

Part (c). From (A12): $d\tau_i / dPA = -\rho / (r_i N_i) - \tau_i (d \ln r_i / dPA + d \ln N_i / dPA)$. The first term is negative. The second has $\tau_i > 0$ and both log derivatives positive (parts a and b), making the parenthetical positive and the whole second term negative. Both terms are negative.

Part (d). From the debt equation, $D_i = G_i - \tau_i (r_i/\rho) N_i - PA_i + i_b D_{i,0}$. Using the budget constraint, $d(\tau_i \mathcal{B}_i)/dPA = dG_i/dPA - 1$, where $dG_i/dPA \leq 0$ (PA reduces locally financed restoration costs or leaves G unchanged). So tax revenue falls: $d(\tau_i \mathcal{B}_i)/dPA \leq -1$. This alone does not pin down debt mechanically (the budget identity holds with equality), but the government re-optimizes: facing a relaxed constraint with lower marginal DWL from the reduced τ (part c) and convex DWL(τ), it reduces both τ and D. The empirical estimate (-16%, $p = 0.04$) strongly

confirms $dD/dPA < 0$.

Part (e). From (A13): $d\ln M_i/dPA = \beta\alpha/K_i^g + (1-\beta)\, d\ln N_i/dPA$. Both terms are strictly positive.

Part (f). From (A10): $d\ln w_i/dPA = \beta(\alpha/K_i^g - d\ln N_i/dPA)$. The sign equals $\text{sgn}(\alpha/K_i^g - d\ln N_i/dPA)$. Empirically, population grows 0.67% while income grows 2.53% per \$100/pc PA, so $\alpha/K_i^g > d\ln N_i/dPA$ by a wide margin. □

Q.6. Welfare derivation

Total welfare is:

$$\mathcal{W}(PA_i) = \underbrace{CS(PA_i)}_{\text{worker surplus}} + \underbrace{\Pi^H(PA_i)}_{\text{landlord surplus}} + \underbrace{\Phi^G(PA_i)}_{\text{fiscal surplus}} - \underbrace{PA_i}_{\text{federal cost}}.$$

Q.6.1. Worker surplus

With logit preferences, aggregate worker surplus is $CS = N \cdot \kappa \cdot \ln[\sum_j \exp(\Lambda_j/\kappa)]$ (McFadden, 1981; Small and Rosen, 1981). For a small county ($N_i/N \approx 0$):

$$\frac{dCS}{dPA} = N_i \cdot \frac{d\Lambda_i}{dPA} = N_i\left[\frac{dw_i}{dPA} - \left(1+\frac{\tau_i}{\rho}\right)\frac{dr_i}{dPA} - \frac{r_i}{\rho}\frac{d\tau_i}{dPA} + \frac{dB_i}{dPA}\right]. \tag{A14}$$

The amenity effect dB_i/dPA is not separately observed, but it is pinned down as the residual of the migration equation: $dB_i/dPA = \kappa\, d\ln N_i/dPA - dw_i/dPA + (1+\tau_i/\rho)\, dr_i/dPA + (r_i/\rho)\, d\tau_i/dPA$. Substituting back:

$$\frac{dCS}{dPA} = N_i \cdot \kappa \cdot \frac{d\ln N_i}{dPA}. \tag{A15}$$

The migration response is a sufficient statistic for worker surplus. It absorbs all channels - wages, rents, amenity, taxes - into a single object, and κ converts it to dollars.

Q.6.2. Landlord surplus

Landlord profits are $\Pi_i^H = (1 - \tau_i/\rho)\, r_i N_i - C(N_i)$. Using $C'(N_i) = r_i$ (the housing supply FOC):

$$\frac{d\Pi_i^H}{dPA} = \underbrace{\left(1 - \frac{\tau_i}{\rho}\right) N_i \frac{dr_i}{dPA}}_{\text{rent appreciation (net of tax)}} + \underbrace{\frac{\tau_i r_i}{\rho} \frac{dN_i}{dPA}}_{\text{tax from new residents}} - \underbrace{\frac{r_i N_i}{\rho} \frac{d\tau_i}{dPA}}_{\text{tax rate windfall}}. \quad \text{(A16)}$$

The first term is the standard Rosen-Roback landlord surplus. The second captures property tax revenue from the expanded housing stock. The third is new: lower τ means landlords retain more of each rent dollar. Since $d\tau/dPA < 0$, the third term is positive.

Q.6.3. Fiscal surplus

The fiscal surplus captures efficiency gains from reduced distortionary taxation and lower debt service:

$$\frac{d\Phi_i^G}{dPA} = \underbrace{-\frac{\partial \text{DWL}}{\partial \tau} \frac{d\tau_i}{dPA}}_{\text{DWL reduction}} + \underbrace{\left(-i_b \frac{dD_i}{dPA}\right)}_{\text{debt service savings}} + \underbrace{\left(-D_i \frac{di_b}{dPA}\right)}_{\text{borrowing cost reduction}}. \quad \text{(A17)}$$

All three terms are positive (Proposition A1: $d\tau < 0$, $dD < 0$; and $di_b/dPA < 0$ from the muni yield result). The deadweight loss of a property tax at rate τ on a base with elasticity ε is $\text{DWL}(\tau) \approx \frac{1}{2}\varepsilon\, \tau^2/(1-\tau)^2 \cdot \mathcal{B}$, with marginal DWL:

$$\frac{\partial \text{DWL}}{\partial \tau} \approx \varepsilon \frac{\tau}{(1-\tau)^2} \mathcal{B}.$$

Q.6.4. Aggregation

Combining equations (A15), (A16), and (A17):

$$\frac{d\mathcal{W}}{dPA} = \underbrace{N_i\, \kappa \frac{d \ln N_i}{dPA}}_{\text{worker}} + \underbrace{\frac{d\Pi_i^H}{dPA}}_{\text{landlord}} + \underbrace{\left(-\frac{\partial \text{DWL}}{\partial \tau} \frac{d\tau}{dPA}\right) + \left(-i_b \frac{dD}{dPA}\right) + \left(-D \frac{di_b}{dPA}\right)}_{\text{fiscal}} - 1. \quad \text{(A18)}$$

The three surplus components do not double-count. Workers gain from higher wages and amenity but lose from higher rents. Landlords gain from higher rents but pay more in property taxes. The government collects more base but charges a lower rate. These transfers cancel in the sum, leaving only net efficiency gains: real productivity and amenity improvements (via migration), housing market capitalization, and reduced fiscal distortion. The formula uses IV estimates as sufficient statistics; the structural parameters α and β do not appear.

Q.6.5. No double-counting: a worked example

Consider a PA dollar that raises house prices by ΔP, lowers the tax rate by $\Delta\tau$, and attracts ΔN new residents. The cross-agent transfers are:

Transfer	Workers pay	Landlords receive
Higher rents	$-N_i \Delta r$	$+N_i \Delta r$
Property tax on new units	$-\Delta N \cdot \tau_i P_i$	-
Tax windfall (lower τ)	$+N_i \cdot \lvert\Delta\tau\rvert \cdot P_i$	$+N_i \cdot \lvert\Delta\tau\rvert \cdot P_i$

In worker surplus, the rent loss and tax relief appear inside the location value change, which the migration response aggregates into $N_i \kappa \, d \ln N / dPA$. In landlord surplus, the rent gain is net of tax, and the tax windfall adds on top. The rent transfer cancels between agents. What remains in the sum is: (i) real productivity and amenity gains from restored K^g (embedded in migration), (ii) housing market surplus from inelastic supply, (iii) DWL reduction, and (iv) debt service savings.

Q.7. Sensitivity of the welfare decomposition

Table 11 in the main text reports the central estimate at κ = \$41,607 (from Diamond 2016, pooled γ = 0.9), ρ = 5%, and ε = 1.0. Tables A18–A21 report sensitivity to each parameter.

The MVPA exceeds \$2.90 per dollar in every parameter combination. The lower bound (\$2.98, at γ = 1.5, ρ = 3%) corresponds to footloose workers in expensive housing markets; the upper bound (\$7.39, at γ = 0.5, ρ = 7%) corresponds to strong location attachment in cheap housing markets. The central estimate is \$4.62 per dollar of PA.

TABLE A18. Welfare sensitivity to κ (migration taste dispersion)

γ	κ	Worker	Landlord	Fiscal	MVPA
0.5	$74,894	$5.03	$1.68	$0.14	$6.86
0.7	$53,496	$3.60	$1.68	$0.14	$5.42
0.9	**$41,607**	**$2.80**	**$1.68**	**$0.14**	**$4.62**
1.1	$34,042	$2.29	$1.68	$0.14	$4.12
1.3	$28,805	$1.94	$1.68	$0.14	$3.76
1.5	$24,964	$1.68	$1.68	$0.14	$3.51

Notes: γ is the pooled logit coefficient on log wages from Diamond (2016). $\kappa = \bar{w}/\gamma$ where $\bar{w}$ = \$37,447 (regression-sample mean PCI, 2010 dollars). Worker surplus = $N_i \kappa \, d \ln N / dPA$, linear in κ. Landlord and fiscal surplus are invariant to κ. ρ = 5%, ε = 1.0.

TABLE A19. Welfare sensitivity to ρ (capitalization rate)

ρ	Worker	Landlord	Fiscal	MVPA
3%	$2.80	$1.17	$0.14	$4.11
4%	$2.80	$1.43	$0.14	$4.37
5%	**$2.80**	**$1.68**	**$0.14**	**$4.62**
6%	$2.80	$1.94	$0.14	$4.88
7%	$2.80	$2.20	$0.14	$5.14

Notes: ρ converts house prices to annual rents ($r = \rho P$) and scales the landlord surplus. Higher ρ (lower price-to-rent ratio) implies larger rent changes per HPI point, increasing landlord surplus. Worker surplus invariant to ρ (it enters the logit only through the migration response, which is estimated). κ = \$41,607, ε = 1.0.

TABLE A20. Welfare sensitivity to ε (DWL elasticity of tax base)

ε	DWL reduction	Fiscal	MVPA
0.5	$0.007	$0.14	$4.62
1.0	**$0.014**	**$0.14**	**$4.62**
1.5	$0.021	$0.15	$4.63
2.0	$0.027	$0.16	$4.64

Notes: The DWL reduction is less than \$0.03 per dollar of PA across the entire range, because the effective property tax rate is low ($\tau \approx 1.72\%$) and DWL scales with τ^2. The welfare decomposition is insensitive to ε. κ = \$41,607, ρ = 5%.

TABLE A21. Full MVPA range across parameter combinations

	ρ				
γ	3%	4%	5%	6%	7%
$\varepsilon = 1.0$					
0.5	\$6.35	\$6.60	\$6.86	\$7.12	\$7.38
0.7	\$4.91	\$5.17	\$5.42	\$5.68	\$5.94
0.9	\$4.11	\$4.37	\$4.62	\$4.88	\$5.14
1.1	\$3.60	\$3.86	\$4.12	\$4.37	\$4.63
1.3	\$3.25	\$3.51	\$3.76	\$4.02	\$4.28
1.5	\$2.99	\$3.25	\$3.51	\$3.76	\$4.02

Notes: Each cell reports the MVPA = worker surplus + landlord surplus + fiscal surplus. The range across all combinations ($\gamma \in [0.5, 1.5]$, $\rho \in [3\%, 7\%]$, $\varepsilon \in [0.5, 2.0]$) is \$2.98 to \$7.39; the MVPA exceeds \$2.90 per dollar in every specification. The result is most sensitive to γ (which governs κ, and thus worker surplus) and ρ (which governs landlord surplus). ε has negligible impact and is held at 1.0 in this table; varying ε shifts each cell by at most \$0.02.